Algorithm Theoretical Basis Document (ATBD) for the Conical-Scanning Microwave Imager/Sounder (CMIS) Environmental Data Records (EDRs)

Volume 11: Vegetation/Surface Type EDR

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1. Abstract

The CMIS Vegetation/Surface Type (VST) EDR will be retrieved by a globally consistent algorithm based on the match between measured emissivity spectral signatures and the standard signatures of each allowed type derived during algorithm calibration. In nominal algorithm operations, the primary inputs are 20 km-scale atmosphere Core Module-retrieved emissivities at 18, 36, and 89 GHz and the snow and ice flag product from the snow cover/depth algorithm. The algorithm uses emissivities to distinguish Dense, Moderate, Sparse, Barren, and Water CMIS aggregate types, the snow and ice flag to identify the Snow and Ice type, and a static database for the Urban type (e.g., Digital Chart of the World). A nearest-neighbor clustering method is the baseline approach for emissivity retrievals and the basis for performance evaluations reported here. However, the retrieval model coefficients and the approach itself are subject to revision commensurate with acquisition of more accurate 20 km scale calibration truth and emissivities and possible future refinements in the retrieved type definitions. Algorithm outputs include the operational EDR product, a current surface condition product, open water fraction, and a surface condition retrieval statistics databases spanning up to one year. In this ATBD we describe the algorithm's physical basis and mathematical and logical structure, inputs, implementation and data flow including integration within overall CMIS processing, and expected retrieval performance based on tests using derived SSM/I emissivities. Performance is expected to meet or exceed all EDR requirements except for probability of correct typing for the Moderate and Sparse types. Algorithm calibration procedures, testing, and operational considerations are also discussed.

2. Introduction

2.1. Purpose

The purpose of this document is to provided all the information necessary to understand, operate, further develop, and use the products from the CMIS vegetation/surface type (VST) retrieval algorithm. The CMIS SRD (NPOESS IPO, 2000) specifies the EDRs' required (threshold level) operational and performance characteristics including definitions, spatial resolution, and measurement range and uncertainty. The integrated VST algorithm (Core Module plus snow cover/depth algorithm plus vegetation/surface type algorithm) meets its nominal performance specifications by deriving all of its products from CMIS brightness temperature observations with the exception of Urban typing. Furthermore, the algorithm reports additional products that extend the retrieval capabilities and aid quality control.

Section 3 summarizes the EDR requirements either specified in the SRD or derived from it. It contains a historical background and physical basis for the proposed algorithm, and it describes the instrument characteristics and data from all sources necessary to meet NPOESS requirements.

Section 4 describes the physical parameterizations relevant to the surface typing algorithm. We also provide algorithm processing flow diagrams including dependencies within the overall processing flow and list input and output fields and ancillary databases.

Section 5 real-data test results and provides measurement uncertainty and other performance estimates based on the tests. These tests are used to demonstrate that the algorithm products will meet its nominal predicted performance specifications. We describe the environmental conditions under which we expect the retrievals to meet requirements, not to meet requirements, or to degrade substantially. We also summarize special constraints, limitations, or assumptions made in algorithm parameterization or testing that may limit the algorithm's applicable domain or necessitate post-launch adjustments based on specific systematic contributions in order to meet performance estimates.

Section 6 discusses algorithm calibration points and outlines the steps necessary to transition algorithm operation from heritage-data to CMIS-data inputs. We outline considerations for pre- and post-launch calibration and validation efforts, including needed measurement capabilities and hardware, field measurements, and existing sources of truth data.

Section 7 describes practical considerations including numerical computation considerations, algorithm quality control and diagnostics, exception and error handling, and archival requirements.

2.2. Document Scope

The *ATBD for the CMIS Vegetation/Surface Type EDR* covers algorithm operations beginning with the ingestion of earth-gridded Core Module products (surface effective broad-band atmospheric window-channel emissivities) and the earth-gridded snow and ice detection flag, and concluding with reporting of the retrieved type and other related algorithm products on the same earth-grid. Preceding sensor data processing steps are covered in the *ATBD for SDR Processing*, *ATBD for the Core Physical Inversion Module,* and *ATBD for the Snow Cover/Depth EDR* (AER, 2000). This ATBD provides outlines for continued algorithm development and advancement and for pre- and post-launch calibration/validation efforts. These outlines are intended to be reviewed and revised prior to launch as new data sources and research become available.

3. Overview and Background Information

3.1. Objectives of the VST EDR retrieval

The VST EDR is a specific measurement that CMIS must perform to complete the mission objectives stated in the SRD: "The mission of CMIS is to provide an enduring capability for providing measurements on a global basis of various atmospheric, land, and sea parameters of the Earth using microwave remote sensing techniques. The CMIS instrument will collect relevant information from a spaceborne platform, and utilize scientific algorithms to process that information on the ground into designated [EDRs]." (SRD, section 3.1.7)

The SRD requires that CMIS retrieve the surface type over global land areas. The CMIS VST algorithm will provide a surface type based on current and archived data for 20 km earth-gridded cells in clear or cloudy (non-precipitating) conditions. Archived data are used to modify cells that are typed as Barren or Water in accordance with the type definitions. The algorithm will also provide the current surface type retrieved without regard for past retrieved types. An additional algorithm module will provide an open water fraction product used internally and by the soil moisture algorithm (see the *ATBD for the CMIS Soil Moisture EDR*, AER, 2000). The surface type product will be useful for monitoring surface factors that affect climate (vegetation, water, and snow cover). The snow and water fraction products will also be useful for providing real-time local conditions whether clear, cloudy, day, or night. The data may be input to regional hydrological and meteorological models as well as long-time-scale climate models.

The 7-type CMIS surface type product will complement a related 17-type EDR required for VIIRS. As discussed below, visible-infrared instruments are better-suited to detailed surface typing (higher resolution and more types) and the impact of cloud cover in VIS-IR retrievals is significant only where surface type changes rapidly (snow cover or flooding) or where there is persistent cloud cover. CMIS typing may be also be useful for constraining or evaluating other microwave retrievals provided that the algorithm is structured such that same-type cells share similar spectral characteristics—that is, surface classes are closely related to spectral classes.

3.2. Summary of EDR requirements

3.2.1. SRD Requirements

The text and tables below are the portions of CMIS SRD section 3.2.1.1.1.1 that apply directly to the VST algorithm. Shading indicates attributes not addressed at all in this document.

Vegetation/Surface Type **TRD App D Section 40.6.4**

Vegetation/surface type is defined as the predominant vegetation type in a given area. Estimation of the percentage of vegetation cover per type in each cell is an objective. The requirements below apply in both clear and cloudy conditions. The following table defines the 17 Vegetation/Surface types required from NPOESS.

Table 3-1: SRD Table 3.2.1.1.1.1, 17 vegetation/surface types required from NPOESS

Land Cover Class	Definition
1. Evergreen Needleleaf Forests	Lands dominated by woody vegetation with a percent cover >60% and height exceeding 2 meters. Almost all trees remain green all year. Canopy is never without green foliage.
2. Deciduous Needleleaf Forests	Lands dominated by woody vegetation with a percent cover >60% and height exceeding 2 meters. Consists of seasonal needleleaf tree communities with an annual cycle of leaf-on and leaf-off periods.
3. Evergreen Broadleaf Forests	Lands dominated by woody vegetation with a percent cover >60% and height exceeding 2 meters. Almost all trees and shrubs remain green all year. Canopy is never without green foliage.
4. Deciduous Broadleaf Forests	Lands dominated by woody vegetation with a percent cover >60% and height exceeding 2 meters. Consists of broadleaf tree communities with an annual cycle of leaf-on and leaf-off periods.
5. Mixed Forests	Lands dominated by woody vegetation with a percent cover >60% and height exceeding 2 meters. Consists of tree communities with interspersed mixtures or mosaics of the other four forest types. None of the forest types exceeds 60% of landscape.
6. Closed Shrublands	Lands with woody vegetation less than 2 meters tall and with shrub canopy cover >60%. The shrub foliage can be either evergreen or deciduous.
7. Open Shrublands	Lands with woody vegetation less than 2 meters tall and with shrub canopy cover between 10-60%. The shrub foliage can be either evergreen or deciduous.
8. Woody Savannas	Lands with herbaceous and other understory systems, and with forest canopy cover between 30-60%. The forest cover height exceeds 2 meters.
9. Savannas	Lands with herbaceous and other understory systems, and with forest canopy cover between 10-30%. The forest cover height exceeds 2 meters.
10. Grasslands	Lands with herbaceous types of cover. Tree and shrub cover is less than 10%.
11. Permanent Wetlands	Lands with a permanent mixture of water and herbaceous or woody vegetation. The vegetation can be present in either salt, brackish, or fresh water.
12. Croplands	Lands covered with temporary crops followed by harvest and a bare soil period (e.g., single and multiple cropping systems). Note than perennial woody crops will be classified as the appropriate forest or shrubland cover type.
13. Urban and Built-Up	Land covered by buildings and other man-made structures.
14. Cropland/Natural Vegetation Mosaics	Lands with a mosaic of croplands, forests, shrubland, and grasslands in which no one component comprises more than 60% of the landscape.
15. Snow and Ice	Lands under snow/ice cover.
16. Barren	Lands with exposed soil, sand, rocks, or snow and never has more than 10% vegetated cover during any time of the year.
17. Water Bodies	Oceans, seas, lakes, reservoirs, and rivers. Can be either fresh or salt-water bodies.

SRDC3.2.1.1.1.1-6 The CMIS instrument shall be capable of discriminating the following aggregated types:

Table 3-2: SRD Table 3.2.1.1.1.1-1, CMIS aggregate types

CMIS Classification	**Land Cover Class**
Dense Vegetation	1-5
Moderate Vegetation	6-9
Sparse Vegetation and Cropland	10,12,14
Barren	16
Urban	13
Snow and Ice	15
Water Bodies and Wetlands	11,17
Not Classified	N/A

Table 3-3: SRD Requirements for the Vegetation/Surface Type EDR

Para. No.		Thresholds	Objectives
C40.6.4-1	a. Horizontal Cell Size	20 km	0.25 km
C40.6.4-2	Not Used	N/A	N/A
C40.6.4-3	b. Horizontal Reporting Interval	(TBD)	(TBD)
C40.6.4-4	c. Horizontal Coverage	Land	Land
C40.6.4-5	Not Used	N/A	N/A
	d. Measurement Range		
C40.6.4-6	1. Vegetation/surface type	8 types in CMIS Classification (Table 3.2.1.1.1.1-1)	17 types (NPOESS requirement)
C40.6.4-7	2. Vegetation cover	N/A	0 - 100 %
C40.6.4-8	e. Measurement Accuracy (veg. cover)	N/A	2 %
C40.6.4-9	f. Measurement Precision (veg. cover)	N/A	0.1 %
C40.6.4-10	g. Correct Typing Probability (vegetation /surface type)	70 %	(TBD)
C40.6.4-11	h. Mapping Uncertainty	5 km	1 km
C40.6.4-12	i. Swath Width	1700 km (TBR)	3000 km (TBR)

In addition to these requirements, the SRD specifies:

1. "Science algorithms shall process CMIS data, and other data as required, to provide the [EDRs] assigned to CMIS." (SRD, paragraph SRDC3.1.4.2-1)
2. "Specified EDR performance shall be obtained for any of the orbits described in paragraph 3.1.6.3 …" (SRDC3.1.6.3-2)
3. "As a minimum, the EDR requirements shall be satisfied at the threshold level." (SRDC3.2.1.1.1-3)
4. "… the contractor shall identify the requirements which are not fully satisfied, and specify the conditions when they will not be satisfied." (SRCD3.2.1.1.1-4)
5. "… CMIS shall satisfy the EDR Thresholds associated with cloudy conditions under all measurement conditions …" (SRD SRDC3.2.1.1.1.1-1)
6. "[The definition of] Probability of Correct Typing [is] probability that a horizontal cell reported as being of type x is in fact of type x, where x is any allowed type." (SRD Appendix A)

Also note that the CMIS system consists "of all ground and spaceborne hardware and software necessary to perform calibrated, microwave radiometric measurements from space and the software and science algorithms necessary to process … these measurement into a format consistent with the requirements of the assigned [EDRs].” (SRD, section 3.1.1)

3.2.2. Requirements interpretations

We infer the following statements as either direct consequences or clarifications of the SRD requirements stated above and take them as requirements to be satisfied by the VST algorithm or to be addressed through algorithm performance evaluation:

1. Cells with no dominant type (for example, equal parts water, dense vegetation, and ice) will be considered unclassifiable for validation purposes.
2. The correct typing probability requirement is met when the correct typing probability for types 1-7 is greater than or equal to 70%. The correct typing probability for the “not classified” type is undefined. Binning the correct typing probability by the true type in tests prevents excessive use of the “not classified” type by penalizing performance when the algorithm types cells which are in fact of type x as “not classified.”

3.2.3. Derived requirements on the vegetation/surface type algorithm

The soil moisture algorithm requires a 20 km earth-gridded water fraction retrieval product with range 0-1 and RMS retrieval error less than 0.15.

3.3. Historical and background perspective of proposed algorithm

Previous passive microwave surface typing algorithms include both generalized retrievals of multiple types and specialized retrievals of a single type (snow cover or wetness). A classification scheme developed for SMMR (Ferraro et al., 1986) included dry land, rain, wet flooded land, dry snow, sea ice, and open water types. The operational SSM/I algorithm (Neale et al., 1990) uses a brightness temperature threshold and decision tree approach to retrieve 12 descriptive classes: Water, dense vegetation, agricultural/rangeland vegetation, arable soil (dry), soil (moist), semi-arid surface, desert, precipitation over vegetation precipitation over soil, composite vegetation and water, composite soil and water/wet soil surface, and snow. The SSMIS algorithm (Aerojet, 1994) is similarly constructed but excludes the precipitation-related types and divides snow into dry, refrozen, and wet categories. Snow's strong brightness temperature signal and its local and global dynamic variability make it a natural objective of passive microwave retrievals. The SSM/I dry snow detection decision tree by developed by Grody (1991) and its successors have been shown to compare well with subjective imagery analysis products, with less than +/-3% total snow covered area difference over the Northern Hemisphere (Grody and Basist, 1996). (See the *ATBD for the Snow Cover Depth EDR*, AER, 2000 for more details on snow detection algorithms.)

Comprehensive surface typing is more commonly accomplished from visible and infrared (VIS-IR) data and there is a larger body of VIS-IR surface typing literature. The International Geosphere Biosphere Programme (IGBP) devised a global land cover classification scheme requiring, among other things, that it be globally exhaustive, that the types be mutually exclusive, and that types are consistently and equally interpretable with either 1 km AVHRR data, higher resolution imagery, or on the ground (Belward, 1996). The 17 IGBP types—which are also the basis for the 17 NPOESS types listed above—were identified to meet these requirements while being within the classification capabilities of AVHRR data (with the exception of urban areas which were meant to be extracted from the Digital Chart of the World, Danko, 1992).

The USGS Global Land Cover Characterization (GLCC) dataset includes the prototype IGBP classification implemented using AVHRR data spanning April 1992-March 1993. (See section

5.5.2 for more details on the data set.) Although heavily reliant on satellite data, the GLCC retrieval methodology is not completely automated and relies on reference data and computer-assisted image processing tools (that is, manual image interpretation) to refine initial multitemporal unsupervised classification results (Belward, 1996, and http://edcdaac.usgs.gov/glcc/globdoc2_0.html). The MODIS Land Cover Product algorithm (Strahler et al., 1996) also retrieves the 17 IGBP type and is completely automated. The MODIS algorithm takes a year's worth of monthly satellite-derived datasets (e.g., vegetation index, surface reflectance) and applies one of three possible retrieval schemes: Decision tree (Brodley et al., 1996; Brodley and Utgoff, 1992), neural net (Gopal and Woodcock, 1996; Moody et al., 1996), or hybrid tree/net. The choice of approach and determination of its weighting coefficients are designed to be a function of periodic calibration against known training sites (Morisette et al., 1998). An additional MODIS product provides change detection based on the year-to-year time-trajectory of the monthly datasets.

3.3.1. Classification techniques

Some techniques commonly used in classification—decision trees, linear discriminant functions, neural nets, and nearest-neighbor clustering—are described briefly below. The main module of baseline VST EDR algorithm uses the clustering approach but takes snow detection inputs from the snow cover/depth algorithm which uses a multivariate decision tree.

Decision tree

A decision tree is a generalized recursive classifier based on a branching logic structure. Beginning from the base (root node) of the tree, a data point is subjected to a series of tests (nodes or splits) each of which may either determine the next test or conclude the sequence by assigning a type (terminal node). Decision nodes may be univariate (based on one input parameter) or multi-variate and can take a variety of forms including linear discriminate functions (LDF) which are threshold tests, nearest-neighbor clustering tests, and neural nets. A decision tree that uses a single algorithm for the splits is termed homogeneous whereas a hybrid decision tree combines two or more algorithm forms (Friedl and Brodley, 1997).

Linear discriminant function (LDF)

An LDF is a binary-decision (yes/no) data test build on logical comparators. For example, the root node of the SSM/I typing algorithm retrieves the water type if TB(22V)-TB(19V) > 4; otherwise, the algorithm continues testing (Neale et al., 1990). Some LDF decision trees—like the SSM/I and SSMIS algorithms—are not exhaustive, meaning that some data points may remain untyped after all tests have been performed.

Neural net

There are a variety of neural network models with different training procedures. A neural net classifier feeds an input variable set through layers of nodes (neurons) that are interconnected (by synapses) that apply weighting coefficients determined through a training process. The last layer is a single node with an encoded representation of the retrieved class. Training procedures for neural net classifiers are discussed in Fischer and Gopal (1992).

Nearest-neighbor Clustering

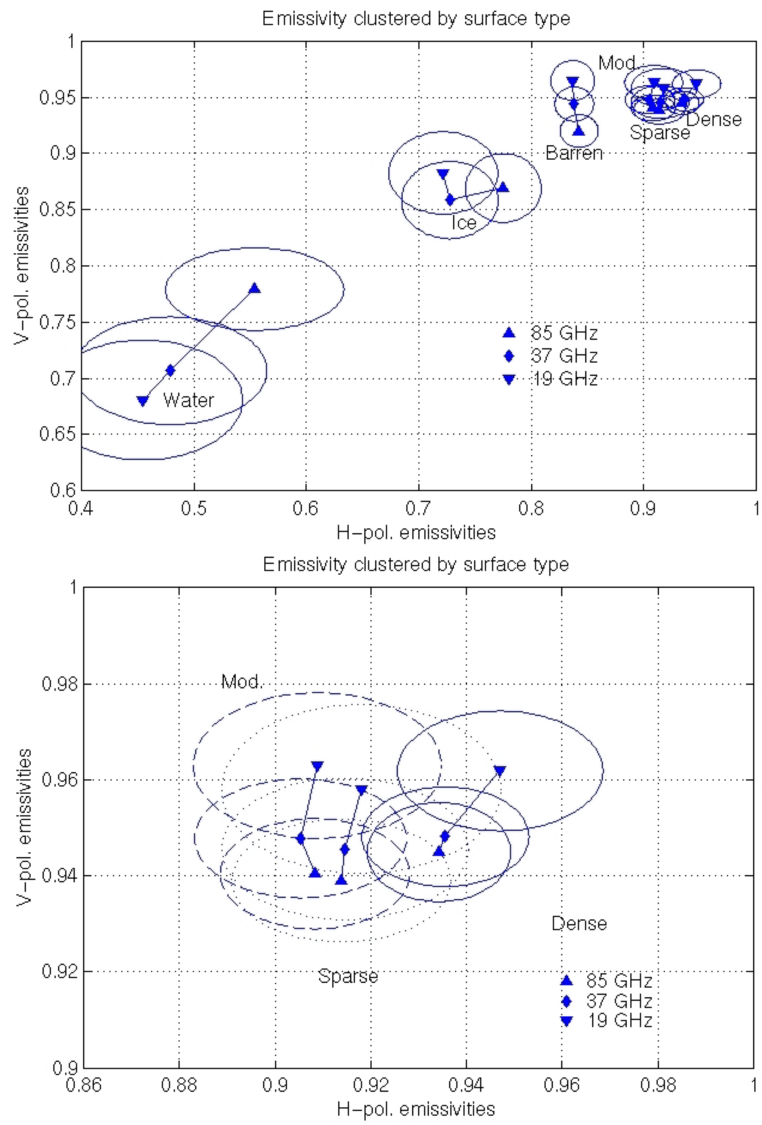
Nearest-neighbor clustering assigns a type based on the distance of the data point from the centroid points (means) of each type defined in the training process. The distance measure may be defined either in the original data space (for example, the six-dimensional space of the 18, 36, and 89 GHz CMIS emissivities *e*) or in a transformation (linear or otherwise) of the space that enhances the isolation of each type. For the VST algorithm, we use the Mahalanobis distance evaluated in retrieved emissivity data space (MathWorks, 1997). Mahalanobis distance is computed using the upper triangular matrix **R** from QR orthogonal-triangular decomposition of the training data (Press et al., 1986). In QR decomposition, any real matrix **A** is decomposed in the form $\mathbf{A} = \mathbf{Q} \cdot \mathbf{R}$, where **Q** is orthogonal and **R** is upper triangular, and $\mathbf{Q} = \mathbf{A} \cdot \mathbf{R}^{-1}$. For all training data matched to type *t*, let **A** be the m_t point rows by *n* data-dimension matrix of deviations from the mean ($e_t - \bar{e}_t$). Use QR decomposition to calculate the *n* x *n* matrix $\mathbf{R}_t$ and normalize by the square-root of m_t-1. Then for each measurement vector **e**, $(\mathbf{e} - \bar{\mathbf{e}}_t)\mathbf{R}_t^{-1}$ is its vector deviation from the centroid of type *t* in orthogonal coordinates; the square root of the sum of squares of the vector components is the Mahalanobis distance. After repeating the calculation for each allowed type, the nearest-neighbor type for the given measurement point is the one with the lowest Mahalanobis distance.

3.4. Physics of Problem

Accurate discrimination of surface type from passive microwave observations requires that the types to be retrieved have distinctive spectral signatures. For example, if a 19V-22V brightness temperature difference greater than 4 K is used to identify standing water (as described above), then any other phenomenon that also produces that signature will be mistyped as water (wet ground perhaps). Conversely, any cell that is nominally water covered but does not produce this signature will also be mistyped. Diverse signatures may occur for the same type for a variety of reasons including 1) mixed types in the cell (50% water, 25% barren, 25% vegetated for example), 2) weather-related phenomenon such as freezing, soil moisture, wind, or water vapor, 3) annually-occurring and other variations in the physical structure of vegetation including green-up, senescence, dormancy, and plant stress, and 4) diversity of the physical structures encompassed by each type definition. Physical diversity within types may be the most significant cause of retrieval ambiguity with the VST EDR type set (Table 3-1 and Table 3-2 above). For example, the Sparse type encompasses croplands, grasslands, and vegetation mosaics with up to 60% forest (> 2 m vegetation) or shrubland (<2 m vegetation) while the Moderate type encompasses savannas and shrublands with between 10 and 60% forest canopy cover and between 10 and 100% shrubland vegetation. These types overlap in terms of the quantitative vegetation characteristics that passive microwave data are most sensitive to—standing biomass or vegetation water content, for example. (Vegetation water content is retrieved quantitatively by the soil moisture algorithm. See the *ATBD for the CMIS Soil Moisture EDR*, AER, 2000.) As discussed above, the 17 IGBP types on which the NPOESS types are based were specifically designed to fit within the limitations of AVHRR data in separating different land cover types from 1 km data. Another definition scheme may be more appropriate to the limitations of passive microwave observations and the goal that classes be mutually exclusive and expressive of surface type variability at 20 km scale.

Figure 3-1 illustrates the passive microwave spectrum's sensitivity to the Dense, Moderate, Sparse, Barren, Ice, and Water types. Each type is represented by a cluster of three points—one for each SSM/I window channel—plotted in V vs. H-pol. emissivity space. The emissivity data come from global monthly-average (July and October) retrievals calculated from SSM/I brightness temperatures, IR satellite skin temperature measurements, and reanalysis atmospheric profiles (Prigent et al., 1998) and the corresponding surface type information is from the Global Land Cover Characterization dataset. (See section 5.5.1 and 5.5.2 for more details.) The points are at the mean values of all the emissivities classified as type X (of 40,000 total) and the ellipses are scaled to match 0.5 times the corresponding standard deviation.

Figure 3-1: Representation of global SSM/I-channel derived emissivity mean and variability by surface type. Symbols are plotted at mean H-pol. and V-pol. emissivity coordinates for each frequency and type. Ellipse dimensions are scaled by 0.5 times the corresponding emissivity standard deviation and encompass 35-60% of the data depending on type and frequency. Top: All types. Bottom: Isolation of Moderate, Sparse, and Dense types.



The clusters for Water, Ice, and Barren types are most clearly separated whereas there is considerable overlap between the Moderate, Sparse, and Dense types (lower plot). Bare ground typically gives lower emissivities than vegetation because of reflectivity due to dielectric contrast (strongest at low frequencies, H-pol., and over moist ground) and volume scattering (strongest at higher frequencies and over dry or frozen ground). As a consequence, the Dense type has the highest H-pol. emissivities at all three frequencies. The fact that the Sparse type falls between the Moderate and Dense H-pol. spectra suggests that, on average, the Sparse type has somewhat less bare ground and more lush vegetation cover than the Moderate type. In fact, the global distribution of the Moderate type (see Figure 5-4) shows that it is often found in dry regions with low-moisture woody vegetation over otherwise mostly bare ground or dry grasses (Australia and the US southwest, for example.) More importantly for typing performance, however, is the fact that the spectra of the Sparse and Moderate types overlap by about 75% and do not have significantly different spectral patterns (like those of Water and Ice types) that could otherwise be used to distinguish them

The seasonal differences in the spectral signature of each type were mentioned above as a source of typing ambiguity. Alternatively, a type's regularly expressed seasonal spectral cycle could be used by a typing algorithm to aid discrimination on an annual basis in an approach similar to that taken by some VIS-IR typing algorithms (discussed above). The baseline CMIS algorithm restricts the use of annual data to cases where the definitions explicitly require it (that is, Barren and Water types, discussed further below) for the following reasons: 1) Some types (namely Snow/Ice) are defined in terms of their instantaneous characteristics, 2) CMIS EDRs are typically retrieved based on instantaneous observations except where multiple observations are required by the nature of the EDR (for example, Sea Ice Edge Motion), 3) Other instruments such as VIIRS can accurately provide retrievals of all 17 NPOESS types at a higher resolution using long-term data with cloudy conditions filtered out, and 4) As retrieved, the CMIS types are mostly spectrally self-consistent (*except* where annual data are used in the retrieval) and may have additional value in discriminating cells based on a degree of green vegetation coverage and thickness.

Some of the of the 17 NPOESS types explicitly include the annual conditions of the vegetation or surface cover in their definitions: 1) The Barren NPOESS type is defined as "Lands with exposed soil, sand, rocks, or snow and never has more than 10% vegetated cover during any time of the year," and 2) The Water Bodies and Wetlands types explicitly exclude non-permanent water cover. (The soil moisture EDR explicitly includes flooding, however.) An accurate classification of these types requires an annual observation cycle to rule out instances of short-term vegetation or water cover. Other types describe vegetation in terms of their annual characteristics; for example, Deciduous Broadleaf Forests "Consists of broadleaf tree communities with an annual cycle of leaf-on and leaf-off periods." The requirements on the vegetation/surface type retrieval should be reevaluated in the future to determine if permanent typing, instantaneous typing, a type-dependent mixture, or multiple products provides the most value to the data's users.

3.5. Instrument characteristics and derived requirements

CMIS is a conically-scanning microwave radiometer with window channels—frequencies chosen to avoid atmospheric absorption lines—around 6, 10, 19, 37, and 88 GHz and atmospheric sounding channel families around 23, 50-60, 60, 166, and 183 GHz. The instrument rotates continuously at 31.6 rpm on an axis perpendicular to the ground taking observations along nearly semi-circular arcs centered on the satellite ground track. Successive arcs scanned by a single sensor channel are separated by about 12.5 km along-track (depending on satellite altitude.) Calibration data is collected from a source (hot) and deep-space reflector (cold) viewed during the non-earth-viewing portion of the rotation cycle. Each observation (or sample) requires a finite sensor integration time which also transforms the sensor instantaneous field of view (IFOV)—the projection, or footprint, of the antenna gain pattern on the earth—into an observation effective field of view (EFOV). The start of each sample is separated by the sample time which is slightly longer than the integration time. The sample time is t_s = 1.2659 ms for all channels with the exception of 10 GHz (exactly $2t_s$) and 6.8 GHz ($4t_s$). All samples fall on one of three main-reflector scan-arcs or a single secondary-reflector scan arc (166 and 183 GHz channels only).

Sensor sample processing (described in the *ATBD for Common EDR Processing Task*, AER, 2000) creates composite measurements which are the spatial weighted superposition of a contiguous group of sensor samples. Although not exact, the process is designed to match observations from different channels to a single reference footprint: The composite fields-of-view (CFOVs) from different channels are more closely matched and collocated than the corresponding EFOVs. In addition, because sensor noise (as measured in NEDT) is both random and independent between samples, the effective NEDT of composite footprints may be reduced (amplified) if the square-root of the sum of squared sample weights is less than (greater than) one. The vegetation/surface type algorithm uses data processed to match 20x20 km reference footprints.

Table 3-4 lists specific characteristics relevant to the VST EDR for each sensor channel. (Sounding channel families around 50-60 and 183 GHz are listed as groups. Other channels that are neither H or V pol. are not listed.) Channels that are applied to VST EDR retrieval are marked either as required to meet or approach threshold requirements (X) or used to meet or approach objectives (O). Additional channels above 18 GHz can enhance performance of the Core Module's emissivity retrieval product.

Table 3-4: Instrument Characteristics and VST EDR Channel Applications

	SELECTED SENSOR CHANNEL SPECIFICATIONS														
Channel prefix	6		10		18		23		36		60VL	89		166	183V
Channel suffix(es)	V	H	V	H	V	H	V	H	V	H	A,…	V	H	V	A,B,C
Frequency range [GHz]	6.45-6.8		10.6-10.7		18.6-18.8		23.6-24.0		36.0-37.0		50-60	87.0-91.0		164.5-167.5	173.4-193.3
VST EDR channel applications[1]					X	X	X	O	X	X	X	X	X	O	O
Single-sample NEDT [K]	0.47		1.2		1.3		1.1		0.66		2.8[2]	0.57		2.7	2.7[2]
20 km composite max/min NRF	--		--		0.39/		0.44/		0.48/		0.41/	0.39/		0.44/	0.40/
Earth incidence angle	55.9		58.3		53.8		53.8		55.9		55.9	55.9		55.7	55.7
Cross-scan EFOV [km]	66.5		46.8		23.1		21.3		16.9		15.0	14.9		17.4	15.5
Along-scan EFOV [km]	40.1		24.9		14.2		13.3		10.8		8.2	8.3		9.6	9.6
Integration time [ms]	5		2.5		1.2		1.2		1.2		1.2	1.2		1.2	1.2
No. EFOV per scan															
Swath width [km]															

[1] X = channel required to meet or approach threshold; O = channel used to meet or approach objectives.
[2] Figures are for lowest frequency in set. For illustrative purposes only.

3.6. Requirements for cross sensor data (NPOESS or other sensors)

The present design of the VST algorithm does not require any data from sensors other than CMIS.

3.7. Required, alternate, and enhancing algorithm inputs
3.7.1. CMIS data and product requirements

Table 3-5: Inputs from other CMIS algorithms

CMIS Products	Usage
Spectral Emissivity from Core Module Algorithm	-Primary VST EDR retrieval input -Required at 18V, 18H, 36V, 36H, 89V, and 89H at 20 km HCS -Required at current time
Prior Vegetation/Surface Type Database from Vegetation/ Surface Type algorithm	-Stored VST statistics database product input for typing of Barren and Water types based on past conditions as per type definitions -Required to be statistically representative of VST retrievals over past year
Snow and Ice Flag from Snow Cover/Depth algorithm	-Determines if cell is Snow and Ice type or not -Required at current time
Precipitation Flag from Core Module Algorithm	-Quality control input -Required at current time, 20 km HCS

3.7.2. Other NPOESS Sensor Data and Product Inputs
No sensor data or products are required from other NPOESS instruments.

3.7.3. External Data Requirements

Table 3-6: External data requirements

External Data	Usage
Surface Database	-Provides static surface data indicating if land is present in cell and if cell is Urban type or not

3.7.4. Alternate and Enhancing Data Sources

Table 3-7: Alternate and enhancing data sources

Data Source	Usage
CMIS: 18V, 18H, 23V, 36V, 36H, 89V, and 89H TBs	-Alternatives to spectral emissivity inputs

4. Algorithm description
4.1. Theoretical description of algorithm
The vegetation/surface type algorithm is based on experimental observations of microwave emissivity spectral signatures of different surface types. As discussed above, these signatures are similarly manifested in sensor-measured top-of-atmosphere brightness temperatures and, although the VST algorithm is expressed in terms of emissivity inputs, it may be easily converted to brightness temperature inputs by changing the algorithm parameters. All of the algorithm modules are empirically-based and require the specification of tunable parameters such as thresholds and coefficient sets. The algorithm currently operates with working values for these parameters whose origin is discussed in section 5.5.

The primary module of the VST algorithm is a decision tree that matches the observed spectrum to one of the spectral signature types corresponding to the Dense, Moderate, Sparse, Barren, and Water surface types. Although we found that a single-node decision tree with a Mahalanobis distance nearest-neighbor clustering approach works best with the test data available, other designs may give better performance with further refinement of the test data and type definitions. In other words, the empirical tuning of the algorithm extends to the choice of algorithm architecture within the constraints of the decision-tree approach.

In addition to the decision tree module, the algorithm includes steps that use snow and ice flag and urban flag inputs, reclassify some cells based on a water coverage fraction calculation, and generation and use of annual surface data memory statistics.

The algorithm's primary inputs are emissivities retrieved by the CMIS Core Physical Inversion Module. The *ATBD for the Core Physical Inversion Module* (AER, 2000) describes this process in more detail. The Core Module removes atmospheric effects and retrieves surface effective emitting temperature T_{eff} and spectral emissivity e from top-of-atmosphere brightness temperature measurements. The Core Module uses a plane parallel model of the atmosphere whose lower boundary condition is parameterized by T_{eff} and e, where $e \equiv 1 - r$ and r is the surface specular reflectivity. The Core Module flags precipitation and passes atmospheric retrieval quality control values that are used by the VST EDR algorithm

Table 4-1 summarizes algorithm design trades leading to the baseline VST algorithm design. The following sections give detailed descriptions of the mathematics of adopted trades and their role in the algorithm processing flow.

Table 4-1: Algorithm design trades

Trade Study	Baseline Decision	Basis/Benefit
Classifier	Single node Mahalanobis distance classifier	Mahalanobis distance method performed better than threshold LDF in real-data tests; single node performed as well as multi-node.
Snow and ice typing	Connect snow and ice typing to snow cover/depth algorithm output	Snow and VST products are consistent at 20 km HCS. Snow and ice algorithm calibration and product validation efforts are focused on snow cover/depth algorithm.
Urban typing	Use static database for Urban typing	Physical reasoning: Urban areas are likely to be indistinct from other types and have wide range of characteristics especially at 20 km HCS. Inclusion of Urban type introduces chance that other types will be misclassified as Urban.
Emissivity-based retrieval	Retrieval is based solely on emissivities	Physical reasoning: Core Module provides accurate emissivities that effectively eliminate temperature and weather signals. Surface condition signal is carried by emissivities.
Gridding	Grid emissivity inputs and retrieve products on grid(s)	Gridded retrievals improve access to prior data for Sparse, Barren, and Water types and interaction with snow and soil moisture algorithms
Use of annual data	Use annual data only for cells typed as Barren and Water	Required to satisfy Barren and Water type definitions; retrieval of other types from current data is either required (Snow and Ice type) or desirable for consistency with most other CMIS EDR products.

4.2. Mathematical Description of Algorithm

Table 4-2 defines vegetation/surface type algorithm inputs and other variables used in this section. The following processing steps occur prior to vegetation/surface type algorithm processing and are described in other documents: Derivation of CMIS brightness temperatures from raw data (*ATBD for SDR Processing*, AER, 2000); footprint matching and interpolation in the sensor reference frame (*ATBD for Common EDR Processing Tasks*, AER, 2000); Core Module retrievals of surface emissivities and effective emitting temperature (*ATBD for the CMIS Core Physical Inversion Module*, AER, 2000); mapping of sensor-gridded data to an earth-grid (*ATBD for Common EDR Processing Tasks*, AER, 2000); and derivation of the snow and ice type detection flag by the snow cover/depth algorithm (*ATBD for the CMIS Snow Cover/Depth EDR*, AER, 2000).

Table 4-2: Definitions of Algorithm Input and Internal Model Symbols

Algorithm Inputs	
eFP or e_i	Emissivity at frequency F and polarization P or channel i
Other algorithm variables	
a_i	Water fraction model coefficient
d_t	Mahalanobis distance for type t
e_t	Mean emissivity parameter for type t
R_t	Upper triangular matrix in QR orthogonal-triangular decomposition of emissivities for type t
e_{w0}	Open water emissivity parameter
e_l	Emissivity of land portion of water-land mixed cell

Each of the following sections provides a mathematical description of a module or component of the CMIS VST algorithm. Some trivial components (namely, programming logic) are excluded. See Figure 4-1 for a processing flow diagram. Note that all of the coefficients and constants are tunable parameters whether or not they are given an explicit value here.

Water fraction calculation

Water fraction is given in terms of emissivities by the following linear model:

$$f_w = a_0 + \sum_N a_i e_i \tag{1}$$

where N nominally encompasses the 18, 36, and 89 GHz linearly polarized channels. At a minimum, the model must include at least one of the 18 or 36 GHz channels. An additional step limits the water fraction to its physical range, 0-1.

Snow and Ice type discrimination

The algorithm types the retrieval cell as Snow and Ice when the snow and ice flag input parameter is 1. No further steps are applied to Snow and Ice typed cells. If the snow and ice flag is 0, then any type except Snow and Ice is allowed. For consistency with the VST EDR definition, the snow and ice flag input should correspond to retrievals of 50% or more snow cover fraction. This flag may differ in some regions from the snow detection binary output product of the snow cover/depth algorithm. See the *ATBD for the CMIS Snow Cover/Depth EDR* (AER, 2000) for more details on how these products are derived.

Urban type discrimination

If the cell is not typed as Snow and Ice and the urban flag input parameter is 1, then the algorithm types the cell as Urban. No further steps are applied to Urban typed cells. Note that when both the urban flag and snow and ice flag inputs are 1, then the cell is typed as Snow and Ice. If both are 0, then any other type is allowed.

Decision tree classification

The single-node Mahalanobis distance decision tree described here is the baseline method for discrimination between the five remaining surface types—Dense, Moderate, Sparse, Barren, and Water. Note that the form of the tree itself and its tests are open to future modification through the algorithm calibration process. A more general form of the algorithm would consist of a multi-node decision tree where each node may be a different type of classifier such as a threshold LDF, a neural net, or nearest-neighbor method. The *ATBD for the CMIS Snow Cover/Depth EDR* (AER, 2001) describes threshold decision tree LDFs for snow cover detection.

The algorithm calculates the Mahalanobis distance measured from the input emissivity point to the mean (or centroid) emissivity point of each type. For type t, the Mahalanobis distance (squared) is given by:

$$d_t = \sum_{i=1}^{N} \left(\sum_{j=1}^{i} \delta e_i \mathbf{R}_{t,ji}^{-1} \right)^2 \tag{2}$$

where each emissivity channel is designated by i and $\delta e_i = e_i - e_{t,i}$ is the difference between the input emissivity and the mean emissivity parameter for type t in channel i. $\mathbf{R}_t$ is the upper triangular matrix from QR decomposition (discussed above) and $\mathbf{R}_{t,ji}^{-1}$ is the jth row, ith column element of its inverse. For each retrieval cell, the algorithm sorts the types from lowest to highest d_t. The retrieved type is then tentatively set to the one matching the lowest d_t. The ordered d_t and matching types are also retained in the algorithm for diagnostic purposes.

Reclassification of water-classified cells using water fraction

The following steps are applied only if a cell is classified as water by the Mahalanobis distance test. If the cell is typed as water but the retrieved water fraction is less than a threshold amount (f_{w0}), then the algorithm assumes that the cell is a two-type mixture (water and land) and estimates the emissivity of the land portion for each channel as:

$$e_l = \frac{e - f_w e_{w0}}{1 - f_w} \tag{3}$$

where e_{w0} is the algorithm's estimate of open water emissivity. The algorithm then repeats the Mahalanobis classification step described above using e_l. If the result of this reclassification is still the Water type, then the algorithm identifies the type matching the *second* closest Mahalanobis distance. If that type is Dense, Moderate, or Sparse then the algorithm returns it as the retrieved type. If second closest type is Barren, the algorithm returns Not Classified as the retrieved type for the cell. This is the only mechanism in the algorithm for picking the Not Classified type. Note that for cells reclassified from water to a another type the algorithm reorders the Mahalanobis distances and the matching types to reflect the change.

Generation of surface data memory

The surface type retrieved up to this point is the current type based on the current measurements. Surface data memory consists of statistical summaries of current type retrievals gathered over daily, weekly, monthly, quarterly, and yearly intervals as described below.

- Current day: Number of occurrences of each type for the Universal Time day up to the current time, for example, 3 Barren, 1 Snow, and 0 occurrences for others out of 4 observations so far.
- Daily summaries: Percentage occurrences of each type for each day up to seven previous days.
- Weekly summaries: Percentage occurrences for each type averaged over up to seven days for up to six previous weeks. A new month starts a new week so a week may have 1 to 7 days.
- Monthly summaries: Percentage occurrences for each type averaged over up to six weeks weighted by number of days in week for up to three previous months.
- Quarterly summaries: Percentage occurrences for each type averaged over three months (DJF, MAM, JJA, and SON) for up to four previous quarters.
- Yearly summaries: Percentage occurrences for each type averaged over four previous quarters.

Use of surface data memory

Surface data memory is used to satisfy the Barren and Water type definitions. (Note that algorithm products include both the VST EDR and the current surface type retrieval which does not take previous retrievals into account.) Annual percentage occurrence up to the current time is estimated as the time-weighted average of one yearly and the current monthly (up to 2), weekly (up to 5), and daily (up to 6) occurrence summaries.

- Barren: If the current retrieved type is Barren, then if the sum of the annual percentage occurrence of Dense, Moderate, or Sparse types exceeds a threshold amount the cell is retyped. If the cell is usually typed Dense or Moderate (>90% of the time, for example) then the cell is retyped Dense or Moderate, whichever occurs most often. Otherwise, the cell is retyped as Sparse.
- Water Bodies and Wetlands: If the current retrieved type is Water, then if the sum of the annual percentage occurrence of all other types except Snow and Ice exceeds a threshold amount the cell is retyped. The new type is the one with the highest annual percentage occurrence (excluding Snow and Ice).

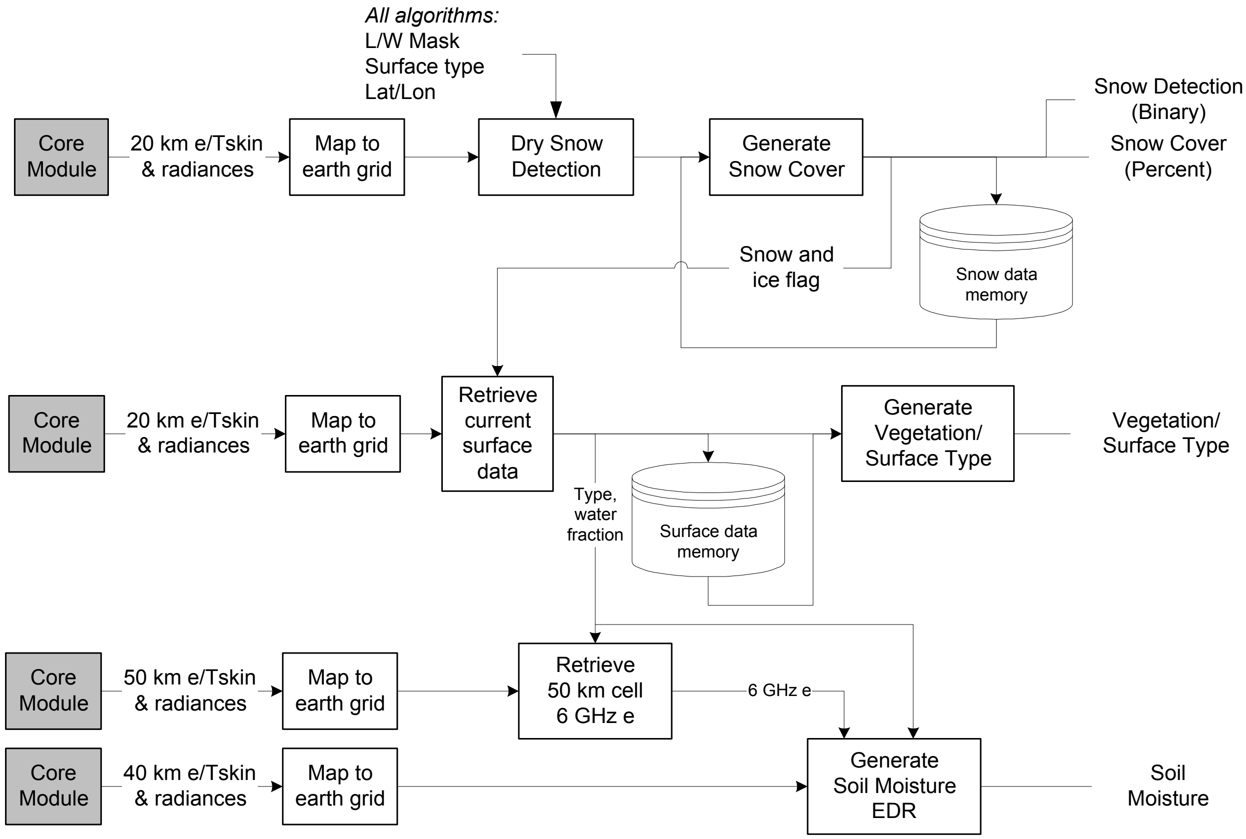
The occurrence thresholds that trigger retyping may be based on probability of correct typing estimates. For example, if the PCT for Barren typing is 70% the threshold may be set at 30%.

4.3. Algorithm Processing Flow

4.3.1. Processing flow for CMIS VST algorithm

Figure 4-1 shows the processing flow for the vegetation/surface type algorithm. Section 4.1 describes algorithm physics and section 4.2 gives the algorithm's mathematical description.

Figure 4-1: VST algorithm processing flow diagram



4.4. Algorithm inputs

The table below summarizes the input data used by the VST algorithm. Input data requirements are described in more detail in section 3.7.

Table 4-3: VST algorithm – Input data description

Input Data	Range
Emissivities @ 18V, 18H, 36V, 36H, 89V, 89H	0-1
Prior vegetation/surface type retrievals	1-8 types in measurement range
Snow and ice flag	One of {0,1}
Urban flag	One of {0,1}
Precipitation flag	One of {0,1}

4.5. Algorithm products

The tables below summarize the characteristics of the operational VST products.

Table 4-4: VST – Operational Product Description

Parameter	Value
Range	1-8 where {1=Dense Vegetation, 2=Moderate Vegetation, 3=Sparse Vegetation and Cropland, 4=Barren, 5=Urban, 6=Snow and Ice, 7=Water Bodies and Wetlands, 8=Not Classified}
HCS	20 km
Units	Unitless type
QC Flag	Low Quality Input Data, Missing Data

Table 4-5: Current surface conditions – Operational Product Description

Parameter	Value
Range	1-8 where {1=Dense Vegetation, 2=Moderate Vegetation, 3=Sparse Vegetation and Cropland, 4=Barren, 5=Urban, 6=Snow and Ice, 7=Water Bodies and Wetlands, 8=Not Classified}
HCS	20 km
Units	Unitless type
QC Flag	Low Quality Input Data, Missing Data

Table 4-6: VST statistics database– Operational Product Description

Parameter	Value
Contents	% occurrence of the eight current surface condition types for past 7 days, 6 weeks, 3 months, and 4 quarters
HCS	20 km

Table 4-7: Open water fraction – Operational Product Description

Parameter	Value
Range	0-1
HCS	20 km
Units	Unitless fraction
QC Flag	Low Quality Input Data, Missing Data

5. Algorithm Performance

5.1. General Description of Nominal and Limited Performance Conditions

This section describes the nominal and limited performance conditions at which the threshold requirements can be achieved. Two SRD sections address special conditions. SRDC3.2.1.1.1-4: "In the event the requirements for an EDR cannot be fully satisfied, the contractor shall identify the requirements which are not fully satisfied, and specify the conditions when they will not be satisfied." SRDC3.2.1.1.1-5: "The contractor shall also specify the conditions under which it recommends delivering an EDR which is incomplete and/or of degraded quality, but which is still of potential utility to one or more users."

The following tables describe the conditions under which nominal predicted performance can be achieved.

Table 5-1: VST – Nominal performance characteristics

Conditions needed to meet threshold requirements	Description	Comments/Characteristics
Atmospheric condition	• Clear or cloudy • Precipitation < 1 mm/hr	Precipitation blocks signal from surface
Surface condition	• Surface type is not Moderate Vegetation or Sparse Vegetation and Croplands	Many Moderate and Sparse surfaces have spectral signatures that more closely match other types, increasing the probability of mistyping

The following table describes the Limited Performance Characteristics under specific conditions; nominal predicted performance may not be entirely achieved under these conditions.

Table 5-2: VST – Performance under limited performance conditions

Conditions	Description	Comments/Characteristics
Precipitation	Precipitation > 1 mm/hr	No retrieval
Moderate Vegetation or Sparse Vegetation and Croplands	Surface type is either Moderate Vegetation or Sparse Vegetation and Croplands	Limited retrieval (degraded correct typing probability)

5.2. Measurement performance estimates

This section details vegetation/surface type performance estimates for each performance metric assigned to the algorithm from the following SRD attributes: *Horizontal Cell Size, Measurement Range,* and *Correct Typing Probability*. Real-data tests with SSM/I-derived emissivity data (described in section 5.5) provide quantitative basis for these algorithm performance assessments. *Measurement Accuracy* and *Measurement Precision* are not addressed here because the algorithm retrieves vegetation/surface type but not retrieve vegetation cover amount.

Of the remaining attributes, *Horizontal Reporting Interval* (in addition to *Horizontal Cell Size*) is derived from the spatial properties of the sensor footprints, footprint compositing and interpolation performance, and grid definition; *Horizontal Coverage* is satisfied through the spacecraft orbit specification and algorithm definitions (that is, the VST retrieval is performed over land by definition), *Mapping Uncertainty* is satisfied by spacecraft stability and instrument pointing error requirements, and *Swath Width* is met primarily through spacecraft orbit and instrument specifications and footprint compositing and interpolation performance. For related algorithm performance assessments, see the *ATBD for Footprint Matching and Interpolation* and the *ATBD for Common EDR Processing Tasks*. Note that Horizontal Cell Size is an explicit part of the assessment of measurement correct typing probability. That is, quantitative performance estimates represent comparisons of retrieved products and true cell-average products.

5.2.1. Binning Categories

Measurement correct typing probability performance is stratified by reporting performance in bins. Each bin represents a range of values for a particular environmental condition. For VST, the natural stratification is by the true surface type condition itself, namely, Dense Vegetation, Moderate Vegetation, Sparse Vegetation and Cropland, Barren, Urban, Snow and Ice, Water Bodies and Wetlands. These bins are mutually exclusive so average global performance can be estimated by combining performance from each bin weighted by the corresponding rate of occurrence of each condition.

5.2.2. Horizontal Cell Size Performance

The CMIS horizontal cell size is the size of a square cell to which the derived EDR value is assigned and against which the EDR product is validated. For vegetation surface type, algorithm performance predictions below are based on the required HCS of 20 km and 20 km is therefore the characteristic HCS of the EDR. Satisfaction of the vegetation/surface type measurement performance requirements at this HCS depends on local spatial characteristics and the horizontal spatial resolution and sampling of the sensor. As shown in Table 3-4, channels used by the VST algorithm range in HSR from about 15 (89 GHz) to 23 (18 GHz) km and footprint matching gives composite footprints ranging from about 15x20 km to 23x20 km. As discussed in section 5.3, our baseline test results at 50 km HCS are derived from SSM/I data with footprints ranging from 15x13 km to 69x43 km. Consequently, mismatch of the sensor HSR and EDR horizontal cell and other spatial errors are already incorporated in the measurement error budget which predicts correct typing probability performance for a 20 km HCS.

5.2.3. Correct Typing Probability Performance

The following table summarizes predicted vegetation/surface type correct typing probability stratified by surface type conditions. The overall value is the sum of each CTP weighted by the corresponding global occurrence. Section 5.3 describes the measurement error budget and assumptions in more detail.

Table 5-3: Vegetation/surface type predicted correct typing probability

Correct Typing Probability [%]	Land cover conditions							Overall
	Dense	Moderate	Sparse	Barren	Urban	Ice/Snow	Water	
Requirement	>70	>70	>70	>70	>70	>70	>70	>70
CMIS total CTP budget estimate	76	57	59	88	90	97	91	70
Global occurrence of condition [%]	18	27	29	11	1	11	3	100

5.2.4. Measurement Range Performance

By algorithm definition, the measurement range for vegetation/surface type includes the seven required surface types—Dense Vegetation, Moderate Vegetation, Sparse Vegetation and Cropland, Barren, Urban, Snow and Ice, Water Bodies and Wetlands—and the Not Classified type. The performance estimates in section 5.2.3 delineate correct typing probabilities (CTP) for each component of this range. The CTP requirement is met for all types except Moderate and Sparse.

5.3. Sensitivity Studies

Table 5-4 gives the derivation of our vegetation/surface type correct typing probability (CTP) predictions summarized above. The baseline errors for Dense, Moderate, Sparse, Barren, and Water conditions are from SSM/I-derived emissivity test results detailed in section 5.5 and include algorithm errors, truth errors, and errors flowing from the spatial match of the truth and sensor-derived data. The emissivity tests fail to meet the >70% CTP requirement for Moderate and Sparse land cover conditions. Derivation of the baseline CTP for Ice/Snow conditions are described in the *ATBD for the CMIS Snow Cover/Depth EDR* (AER, 2000). See section 5.5.5.6 for a partial test of Ice/Snow retrievals (only permanent Ice was tested) using an approach that differs from the snow cover/depth algorithm. The baseline CTP for Urban conditions is an assumed value for the accuracy of the external data source used to provide a global Urban type map (for example, the Digital Chart of the World). In order to meet these requirements, we assume that the following improvements will be realized for CMIS retrievals.

- Truth data adjustment: 2-5% CTP improvement. As discussed below, the CTP of the test truth data for CMIS aggregate types at 1 km scale is probably better than 80%. At 50 km scale, 7% of the cases tested had typing ambiguities and 2.3% were unclassifiable. Improvements are expected to be greater for types with the most ambiguities (Moderate and Sparse).
- 20 km CMIS HSR v. 50 km test HSR: 2-5% CTP improvement. In tests, CTP performance was best for cells with homogeneous types and more mixed cells are observed at larger cell sizes than smaller. Improvements are expected to be greater for types that contain mixtures (Sparse and Moderate) and for the Water since more all-water cells will be observed and errors are highest with mixed land-water cells.
- Footprint matching: 2-5% CTP improvement. Test emissivities derived from SSM/I data had HSR ranging from about 15 to 70 km with ellipsoidal footprints whereas CMIS footprints will be well-matched to 20 km in one dimension and will span about 17-23 km

in the other. Better footprint matching improves the ability of the sensor to match cell type from the measured spectrum. Improvements are expected to be highest for Moderate and Sparse types and around water bodies where spatial heterogeneity in the emissivity spectrum is highest.

- Geolocation: No CTP improvement predicted. Absolute geolocation errors will be better for CMIS than SSM/I but they may not be much better relative to the HSR. Also, since the emissivity data used to derive test results were monthly averages, any single-measurement geolocation errors are reflected on average in the match between the sensor footprint and the truth cell. The budget adjustment due to errors of this type are given above.

Table 5-4: Vegetation/surface type correct typing probability estimation error budget

Error category	Budget adjustment	Land cover conditions						
		Dense	Moderate	Sparse	Barren	Urban	Ice/Snow	Water
Test results	Baseline CTP	70	42	44	82	90	97	79
Errors in test truth data & evaluation	Not a part of CMIS errors	2	5	5	2	0	0	2
20 km CMIS HSR v. 50 km test HSR	CMIS better than test	2	5	5	2	0	0	5
Footprint matching	CMIS better than test	2	5	5	2	0	0	5
Geolocation	CMIS better than test	0	0	0	0	0	0	0
CMIS total CTP budget estimate	Baseline plus CMIS improvements	76	57	59	88	90	97	91
Requirement		>70	>70	>70	>70	>70	>70	>70

5.4. Constraints, Limitations, and Assumptions

- Measurement performance predictions are predicated on the assumptions summarized in the error budget table above. Namely, we assume that CMIS performance will benefit from the higher CMIS spatial resolution, smaller HCS, and reduced spatial representativeness errors from footprint matching compared to the SSM/I-derived emissivity tests detailed in section 5.5.

5.5. Algorithm performance tests with similar sensor data

5.5.1. Emissivity dataset

The vegetation surface type algorithm was applied to a global emissivity dataset derived from SSM/I 19.35V/H, 22.235V, 37V/H, and 85.5V/H GHz observations by Prigent et al. (1998). Global emissivity maps at selected channels are given in Appendix 1—Emissivity dataset. Prigent used a radiative transfer model to calculate emissivity given atmospheric and surface parameters. Data from ISCCP (International Satellite Cloud Climatology Project) analyses of visible and infrared satellite observations provided cloud detection and surface skin temperature estimates at the 30 km resolution of the ISCCP DX datasets. NCEP reanalysis provided atmospheric profiles at 2.5° resolution in latitude and longitude. Emissivity is derived for cloud-free and thin, high cloud cells in the DX data sets where SSM/I and ancillary data are available. Monthly average emissivity and its standard deviation for July and October, 1992, are reported for each cell with a sufficient number of retrievals per month. The July and October datasets contain 184,223 and 185,419 non-ocean reports, respectively, with an additional 114,659 and 115,272 ocean reports covering high latitudes only.

Surface temperature and atmospheric parameters are the primary error sources in the emissivity database. Prigent et al. (1997) estimates that the ISCCP surface temperature estimation error is ≤ 2 K which leads to an emissivity retrieval error estimate ≤ 0.007 (per observation) assuming no atmosphere, 0.9 emissivity, and 258 K surface temperature. As an indication of atmospheric errors, the monthly average standard deviation over all land reports is 0.018 at 19V and 0.021 at 22V suggesting at least 0.01 additional RMS error contribution due to atmospheric effects at 22 and 85 GHz and less at 37 GHz. Other error sources include mismatched geolocation, spatial resolution, and temporal sampling between SSM/I and ancillary observations. On average, each emissivity report is based on about 33 observations per month with a commensurate reduction in random errors. Residual systematic errors include a fixed IR emissivity assumption, local reanalysis bias, and observation timing. Based on this analysis, we assume that the net emissivity characterization error or the dataset is about 0.005-0.01.

The Prigent dataset is a good surrogate for CMIS-retrieved emissivities in performance testing for several reasons. Firstly, it represents most of the useful spectral range of CMIS that will be available for 20 km HCS retrieval. Second, its measurement uncertainty is comparable to or greater than that expected for CMIS emissivities at the same channels (~0.005). Lastly, the Prigent dataset is globally representative and covers two months at the peak and declining stages of the Northern Hemisphere vegetation cycle.

5.5.2. Global Land Cover Characterization dataset

For evaluation of the vegetation/surface type algorithm, we have adopted the 1 km resolution USGS Global Land Cover Characterization (GLCC) data set (http://edcdaac.usgs.gov /glcc / glcc.html). The GLCC is derived from AVHRR data spanning April 1992 through March 1993. The data are presented in several thematic map types including the International Geosphere Biosphere Programme (IGBP) Land Cover Classification (Belward, 1996), which we use here. The IGBP types are nearly identical to the 17 NPOESS required types (Table 3-1) with the exceptions that the order of types 2 and 3 are reversed, type 11 is lands with a permanent mixture of water and herbaceous or woody vegetation "that cover an extensive area," and type 15 is lands under snow and/or ice cover "throughout the year." Belward (1996) also notes that the Urban class "will not be mapped from AVHRR imagery but will be developed from the populated places layer that is part of the Digital Chart of the World (Danko, 1992)." These differences have no practical effect in our tests because 1) the CMIS aggregation lumps types 2 and 3 together in Dense Vegetation and types 11 and 17 together in Water Bodies and Wetlands, 2) snow detection performance was evaluated separately in the *ATBD for the CMIS Snow Cover/Depth EDR* (AER, 2000), and 3) there is insufficient data to test Urban class retrievals.

The accuracy of the 1 km GLCC data set has not been fully evaluated. One test reported 79% correct typing probability (CTP) for cells with unambiguous true type as determined by evaluation of high-resolution imagery (Scepan, 1999). If ambiguous cells were included–that is, if the interpreters could not agree on the true type then the retrieval for that cell was automatically counted as wrong–the CTP fell to 67%. In addition, the recent update of the data set to version 2 changed the type in about 10% of the cells. Since presumably ambiguities occur mostly between like types, we assume that the dataset's ability to identify the CMIS aggregate types at the 1 km scale is somewhat better than 80%. However, as discussed below, reevaluation of the CMIS aggregate type at the SSM/I ~50 km scale introduces additional ambiguities that may add to the overall vegetation/surface type algorithm retrieval error estimates.

5.5.3. Evaluation of true CMIS aggregate type at SSM/I emissivity scale

We used the following process to evaluate the CMIS aggregate type at the scale of the Prigent SSM/I emissivities. A nominal 50 km HCS was chosen based on SSM/I HSR at 15, 37, and 70 km, emissivity cell growth due to monthly averaging of non-coincident observations, and emissivity-open water fraction correlations at various cell sizes. For the coordinates of a given emissivity cell, the fractional coverage of each of the 17 IGBP types was calculated from GLCC data falling within the surrounding 50 km HCS. We then determined the CMIS aggregate type by two methods. In the first method, the fractions of each IGBP land cover class matching each one of the 7 main CMIS aggregate types (Table 3-2) were summed. This yielded one overall fraction for each of the 7 CMIS aggregate classes. The cell was then assigned a *dominant type* equal to the CMIS aggregate class with the highest fractional coverage, now called the *dominant type fraction*. A drawback of this method is that many of the IGBP (and NPOESS) types have specific restrictions on the coverage mix in the cell that may be incompatible with the dominant type definition. For instance, the Barren class is restricted to lands that never have more than 10% vegetated cover but at cell with >50% Barren 1 km IGBP coverage is flagged as the Barren CMIS aggregate type by the dominant type method.

Consequently, we also evaluated the CMIS aggregate type by a second method that tries to take account of the mixed fractions of IGBP types in the 50 km cell and the IGBP and CMIS aggregate type definitions. We apply the following decision sequence to determine a single *aggregate type* where F(A-B) is the sum of the fractions of IGBP type A through B. The sequence terminates when a type is found:

1. If $F(11) + F(17) \geq 0.5$ then TYPE = Water
2. If $F(15) \geq 0.5$ then TYPE = Ice
3. If $F(13) \geq 0.5$ then TYPE = Urban
4. If $F(1\text{-}5) \geq 0.6$ then TYPE = Dense
5. If $F(1\text{-}10) + F(12) + F(14) < 0.1$ then TYPE = Barren
6. Define MODINDEX = $F(6\text{-}7) + 0.6{*}F(8) + 0.3{*}F(9)$. If MODINDEX > 0.5 then TYPE = Moderate
7. If $F(10) > 0.6$ and MODINDEX < 0.1 then TYPE = Sparse
8. If $F(14) > 0.6$ then TYPE = Sparse
9. If $F(1\text{-}5) > 0$ and $F(6\text{-}9) > 0$ and $F(10) > 0$ and $F(12) > 0$ then TYPE = Sparse
10. If no type has been identified and the dominant type fraction ≥ 0.5 then TYPE = dominant type
11. Otherwise, TYPE = Not Classified.

Much of the *ad hoc* nature of this decision sequence is due to the fact that the IGBP type definitions are designed for 1 km typing. Besides the complications of transferring 1 km types to 50 km, the type definitions themselves are not easily transferred in some regions because of differences between the mix of surface types typically observed within 1 and 50 km cells. Of 20,000 locations analyzed, the aggregate type differed from the dominant type in 1,414 or 7%. 475 cells or 2.3% were not classified. Because the aggregate type method does not provide a type fraction, the corresponding dominant type fraction is used in its place in our tests.

5.5.4. Testing procedure

Beginning with the July and October emissivity datasets, we identified 184,000 land locations common to each. Of these, 20,000 were randomly chosen and at each of these points the 50 km "true type" was determined by the procedure above. Additionally, the fractional coverage of each CMIS type was calculated for each cell. Since snow classification could not be easily tested with this dataset, a simple emissivity-based snow detector was used to retype some cells (335 in July and 1455 in October) as Not Classified if snow was detected and the true type was not already determined to be ice (see *ATBD for Snow Cover/Depth EDR*, AER, 2000). Also, October cells typed as water at latitudes above 60N were retyped as ice.

Mutually exclusive algorithm training and test sets were required to complete each test of the vegetation/surface type algorithm. A customary classification algorithm procedure is to reserve 25% of a dataset for testing and use the rest for training. Of the 75% of the data available for training, a large portion was typically removed by tests on the true type data in order to provide the most accurate data on which to train. Data were not used for training if 1) the true type was Not Classified, 2) the true type was not to be retrieved (see cases below), and most importantly 3) the dominant type fraction was greater than 95%. To reduce the random error in the estimates of retrieval performance, we repeated the random selection of training and test data five times per case. We then calculated the performance metrics from the combined set of five retrieval runs and their matching true types.

5.5.5. Test results

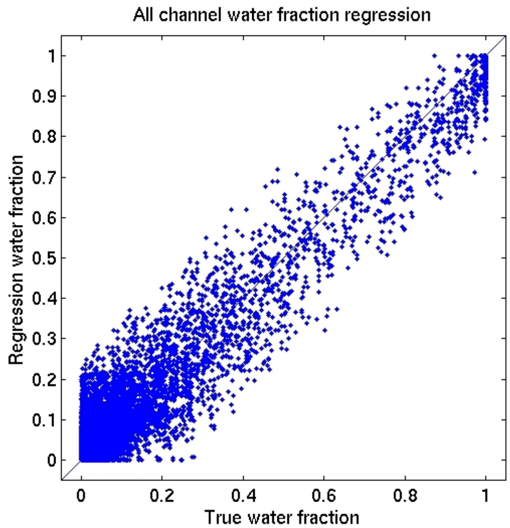
5.5.5.1 Water fraction regression

The vegetation/surface type algorithm includes water fraction estimation from a linear emissivity regression model. We regressed the global water fraction truth against the seven SSM/I emissivities for cells with greater than zero true water fraction. Figure 5-1 shows the scatterplot of true and model-retrieved water fraction and Table 5-5 summarizes the measurement uncertainty results. We expect CMIS to provided as good as or better performance primarily because it will have significantly less range in spatial resolution between the contributing channels. The retrieval could also be refined by regionalizing the model or differentiating the model depending on the prevailing non-water type in a region.

Table 5-5: Water fraction emissivity regression

	Open water fraction range				
	>0-0.2	0.2-0.4	0.4-0.6	0.6-0.8	0.8-1
Measurement uncertainty	0.047	0.102	0.105	0.106	0.079
No. in range	11215	784	331	208	431

Figure 5-1: Water fraction regression scatterplot



5.5.5.2 Baseline retrieval test

The emissivity module of the vegetation/surface type algorithm retrieves the Dense, Moderate, Sparse, Barren, Water, and Not Classified CMIS aggregate types. The Ice/Snow type is retrieved by the snow cover algorithm and this product is a vegetation/surface type algorithm input. Ice/Snow type retrieval performance is reported in the *ATBD for the CMIS Snow Cover/Depth EDR* (AER, 2000). (In a later section, we add the Ice type as a retrievable in the emissivity module and retest retrieval performance.) The Urban type is not included in these tests because the vegetation/surface type algorithm uses a static database input to flag Urban cells and the 50 km test dataset included no Urban cells.

The baseline retrieval test uses a single set of algorithm parameters for retrievals from July and October emissivities (40,000 total data points). Retrieval performance for this case is summarized in the following tables. Results are based on five realizations of the train-test sequence. Using the first realization as an example, 14,132 training cells were used of 18,950 that met the 95% dominant type fraction threshold, were not flagged as snow (1,790), were not of type Ice (4,107), and were not of ambiguous true type (1,010). For testing, 8,579 cells were used of 34,103 that were not flagged as snow (1,790) and were not of type Ice (4,107).

Table 5-6 summarizes retrieval performance using the correct typing probability (CTP) metric. With this metric, the fraction correct is the number of cells correctly retrieved as type X over the number of cells retrieved as type X. The table gives the average CTP for each condition (that is, the true type) where the average CTP is the number of cells correctly retrieved as type X over the number of cells of type X tested. No overall CTP is given because the Ice type is not included in the test. Although the Not Classified type is retrieved by the algorithm only as a quality control factor (the true Not Classified type bears no relation to the retrieved Not Classified type) the table includes result for Not Classified for completeness. Only 2% of cells overall are typed as Not Classified by the algorithm.

Table 5-6: Baseline algorithm correct typing under nominal conditions

Conditions	Dense	Moderate	Sparse	Barren	Water	Not Clsf'd
Avg. CTP [%]	70	42	44	82	79	11
99% conf. interval [%]	+/-2	2	1	2	3	3
No. tested	8806	12782	13433	5326	1208	1017
% of total	21	30	32	13	3	2

Table 5-7 gives the full retrieval confusion table. Each value is the percentage of tested cells of "true type" (left column) that were retrieved as "retrieved type" (top row). The strongest mistyping is between types that have overlapping physical characteristics—Dense, Moderate, and Sparse vegetation, for example. 11% of Moderate cells—a type which includes shrublands and savannas with little lush vegetation and a high percentage of dry, bare terrain—are typed as Barren and 8% of Barren cells are typed as Moderate. And Sparse cells—which includes grasslands, agricultural areas, and vegetation mosaics that are sometimes lush—are more likely to be mistyped as Moderate or Dense than Barren.

Table 5-7: Confusion table for baseline algorithm under nominal conditions

True type	% of cells that are in fact true type reported as						No. tested	% of total
	Dense	Moderate	Sparse	Barren	Water	Not Clsf'd		
Dense	70	12	16	0	0	1	8806	21
Moderate	24	42	21	11	0	2	12782	30
Sparse	19	30	44	3	1	2	13433	32
Barren	1	8	6	82	0	3	5326	13
Water	3	5	7	1	79	4	1208	3
Not Clsf'd	18	24	29	13	5	11	1017	2
No. retr.	12128	11241	10731	6340	1146	986	42572	
% or total	28	26	25	15	3	2		

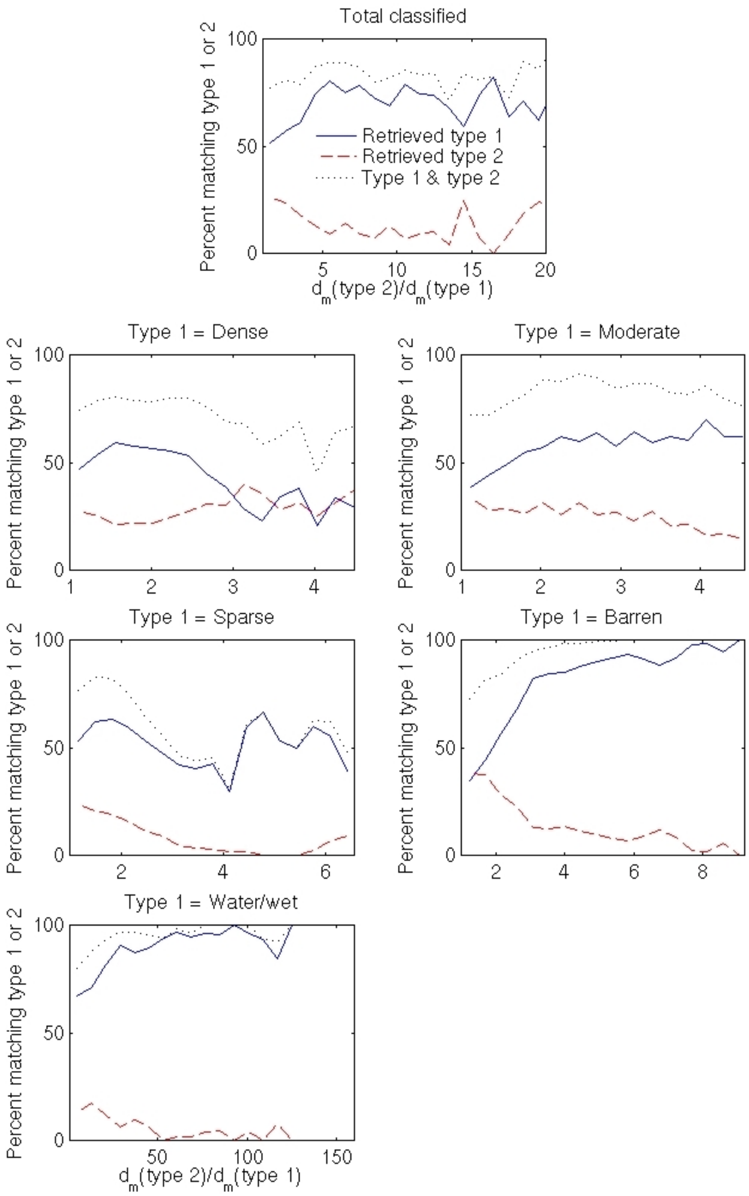
Table 5-8 shows the confusion table with the positions of retrieved and true types reversed. Here, the overall average CTP across all cells *retrieved* as type X is given. For example, 51% or cells retrieved as Dense are correct; 25% are in fact Moderate, and 22% are Sparse. This approach is useful for quality control but does not indicate global CTP performance because performance is weighted by the distribution of cells among the retrieved types, not by the global distribution of true types. In this test Not Classified cells—which originate because of apparently false-positive Water typing—are distributed among all the true types roughly in proportion to their occurrence in the truth dataset. We have also tested more selective algorithm implementations that put a greater number of ambiguous cells into the Not Classified type using the Mahalanobis distance as an indicator of retrieval confidence. With this approach, the CTP averaged across all cells *retrieved* as type X (as in Table 5-8) is improved because fewer cells are retrieved as type X and only the retrievals most likely to be correct are retained. But the CTP averaged across all cells with a common true type condition (as in Table 5-6 and Table 5-7) is degraded because many cells that were correct but ambiguous are set to Not Classified on the basis of the confidence measure. In contrast, in our baseline approach, global correct typing performance based on the true type distribution is optimized and the number of cells retrieved with the Not Classified type is minimized.

Table 5-8: Confusion table normalized by retrieved cell counts

Retrieved type	% of cells reported as retrieved type that are in fact						No. retrieved	% of total
	Dense	Moderate	Sparse	Barren	Water	Not Clsf'd		
Dense	51	25	22	0	0	2	12128	28
Moderate	10	47	36	4	1	2	11241	26
Sparse	13	26	55	3	1	3	10731	25
Barren	0	22	7	69	0	2	6340	15
Water	0	3	7	2	84	5	1146	3
Not Clsf'd	11	23	32	16	5	11	986	2
No. true	8806	12782	13433	5326	1208	1017	42572	
% of total	21	30	32	13	3	2		

Figure 5-2 illustrates the value of the Mahalanobis distance d_m as a measure of correct typing confidence. For each retrieval cell, the algorithm's emissivity module calculates the distance d_m for each of the five possible retrieved types (excluding Not Classified type). The retrieved type is the type with the smallest d_m (type 1). Let's call the type with the second smallest d_m type 2. Then the ratio d_m(type 2)/d_m(type 1) reflects how strongly the two types are differentiated. In Figure 5-2, the correct typing probability is given as a function of the d_m ratio (type 1 curves). In each case (overall and by retrieved type) the CTP increases as the d_m ratio increases from 1. At the same time, the percentage of cells in which type 2 is the true match typically decreases as the d_m ratio increases, and the percentage in which one of the two types is correct increases. Overall, the CTP increase by about 25% (from 50 to 75%) as the d_m ratio increases from 1 to 5 and the correct match percentage of type 2 decreases from 25 to about 10%.

Figure 5-2: Type matching percentage as a function of Mahalanobis distance (d_m) ratio for closest d_m type (type 1), second-closest type (type 2), and sum of type 1 and 2



The d_m ratio is a good indicator of retrieval confidence for the Moderate, Barren, and Water types but is less valuable for Dense and Sparse. As reflected in Figure 3-1 (and in the CTP in Table 5-6), Water and Barren types are the most spectrally distinct groups and where d_m(type 1) is low compared to type 2 there is a *low* probability that type 1 is wrong if type 1 is Water or Barren. In contrast, the Dense, Moderate, and Sparse types are spectrally close and overlap considerably; many true Sparse cells, for example, may have significantly lower d_m(Dense) than d_m(Sparse) and the Dense CTP actually *decreases* with d_m ratio above about 1.5. Some of the lowest ratios occur where both d_m(Dense) and d_m(type 2) are high—that is, for spectral outliers. For the high-emissivity Dense type, the spectral outliers are the highest emissivity cases, many of which are most likely to be Dense (see Figure 3-1). When the d_m ratio is high, the spectrum may be close to the mean Dense spectra but the likelihood increases that it is a Sparse or Moderate cell with a Dense-like spectrum. Similarly, CTP in Sparse-retrieved cells does not follow the d_m ratio because the mean Sparse spectrum falls between the Dense and Moderate types.

5.5.5.3 Retrieval test for separate July and October models

In this test, the baseline retrieval configuration is used but the train-test sequence is applied separately to the July and October emissivity data sets (20,000 points each). As above, results are based on five realizations of the train-test sequence.

The following tables summarize the July and October algorithm results. The Dense type is retrieved more accurately in October than July because many vegetation types are at the peak of their seasonal cycle in the Northern Hemisphere in July and therefore there is even greater spectral overlap between Dense, Sparse, and Moderate cells, as shown in Figure 5-3. In July, the Sparse type—which includes agricultural lands, grasslands, and mosaics—attracts a large number of both true-Moderate and Dense cells because the Sparse type falls "between" the two types spectrally and its spectral mean is therefore likely to be closer to the spectrum of many non-Sparse cells. Section 3.4 discusses the potential for using the seasonal differences in the spectral signature of each type to aid type discrimination on an annual basis.

Table 5-9: Correct typing, July train and test

Conditions	Dense	Moderate	Sparse	Barren	Water	Not Clsf'd
Avg. CTP [%]	58	35	63	77	69	9
99% conf. interval [%]	+/-2	2	2	2	4	4
No. tested	4488	6760	6932	2746	786	567
% of total	20	30	31	12	4	3

Table 5-10: Confusion table, July train and test

True type	% of cells that are in fact true type reported as						No. tested	% of total
	Dense	Moderate	Sparse	Barren	Water	Not Clsf'd		
Dense	58	10	31	0	0	1	4488	20
Moderate	19	35	35	10	0	1	6760	30
Sparse	11	20	63	4	1	2	6932	31
Barren	1	7	12	77	0	3	2746	12
Water	5	6	13	1	69	6	786	4
Not Clsf'd	11	19	43	11	7	9	567	3
No. retr.	4761	4494	8800	3087	640	497	22279	
% or total	21	20	39	14	3	2		

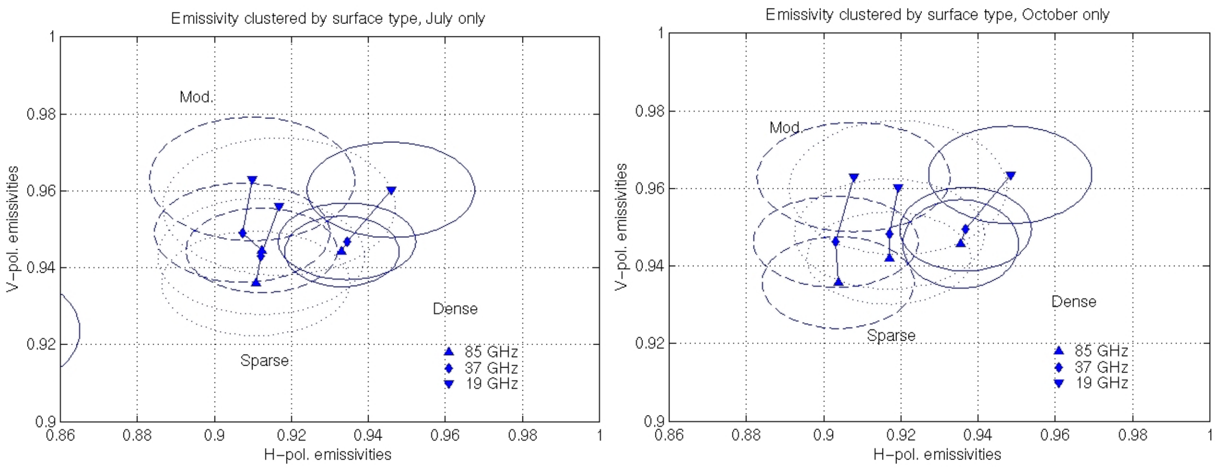
Table 5-11: Correct typing, October train and test

Conditions	Dense	Moderate	Sparse	Barren	Water	Not Clsf'd
Avg. CTP [%]	78	50	36	86	82	7
99% conf. interval [%]	+/-2	2	2	2	4	4
No. tested	4341	5872	6790	2530	593	504
% of total	21	28	33	12	3	2

Table 5-12: Confusion table, October train and test

True type	% of cells that are in fact true type reported as						No. tested	% of total
	Dense	Moderate	Sparse	Barren	Water	Not Clsf'd		
Dense	78	12	9	0	0	1	4341	21
Moderate	26	50	12	11	0	1	5872	28
Sparse	26	33	36	3	1	2	6790	33
Barren	0	10	1	86	0	3	2530	12
Water	3	7	4	1	82	4	593	3
Not Clsf'd	25	23	18	17	9	7	504	2
No. retr.	6818	6066	3683	3121	598	344	20630	
% or total	33	29	18	15	3	2		

Figure 5-3: Representation of global SSM/I-channel derived emissivity mean and variability by surface type for July and October (see Figure 3-1 caption)



5.5.5.4 Retrieval tests with merged Sparse and Moderate types

In this test, the baseline retrieval configuration is used with data from both months but Sparse and Moderate data are combined into one type in algorithm test and training and only 4 types—Dense, Moderate/Sparse, Barren, and Water—are retrieved. As above, results are based on five realizations of the train-test sequence. The confusion matrix is given in Table 5-13. Compared to the baseline results (Table 5-7) the Dense, Barren, and Water types are retrieved with the same CTP and the combined Moderate/Sparse type is retrieved more accurately than either of the types were separately. The exercise demonstrates that at least three degrees of vegetation cover (Dense, Moderate/Sparse, and Barren) can be retrieved with at least about 70% CTP.

Table 5-13: Confusion matrix for retrieval with Moderate and Sparse types combined

True type	% of cells that are in fact true type reported as					No. tested	% of total
	Dense	Mod./Sparse	Barren	Water	Not Clsf'd		
Dense	70	29	0	0	1	8839	21
Mod./Sparse	22	69	7	0	2	26139	61
Barren	1	15	81	0	3	5406	13
Water	3	12	1	80	4	1268	3
Not Clsf'd	19	54	12	6	9	1023	2
No. retr.	12134	22149	6322	1201	869	42675	
% or total	28	52	15	3	2		

5.5.5.5 Retrieval tests with added emissivity measurement noise

In this test, the baseline retrieval configuration is used with data from both months. Normally-distributed random noise is added to the test emissivity set (not the training set) with 10 replications. That is, the test data are replicated 10 times for each test with a different noise realization added each time. As above, results are based on five realizations of the train-test sequence. The results are given in Table 5-14 for the baseline case and added noise with 0.005, 0.01, and 0.02 standard deviation. As discussed above, we estimate that the month-average Prigent emissivity set has an error of representativeness of about 0.01. With this background variance, additional error up to 0.01 has limited impact on retrieval performance. At the 0.02 added noise level, there is more significant degradation in CTP especially among the already highly-overlapping Dense and Sparse types. Since the predicted CMIS emissivity retrieval uncertainty for the 18, 36, and 89 GHz channels is less than 0.01, we do not budget for additional typing error due to the CMIS emissivity retrieval error.

Table 5-14: Correct typing with added emissivity measurement noise

Emissivity noise added to inputs	Total input emis. error estimate	% correct typing probability for true type condition				
		Dense	Moderate	Sparse	Barren	Water
0	0.010	70	42	44	82	79
0.005	0.011	69	43	43	82	79
0.01	0.014	68	43	44	81	78
0.02	0.022	54	47	40	81	80

5.5.5.6 Retrievals maps (including Ice/Snow retrieval)

We added the Ice type added to the Mahalanobis classifier in order to generate comprehensive retrieval maps for the July and October emissivity data sets. Table 5-15 gives the confusion matrix for the retrieval when Ice is included. As before, results are based on five realizations of the train-test sequence and July and October data are used together in algorithm training. Note that we continue to exclude from the test normally ice-free cells where snow was suspected based on an emissivity threshold test. However, some cells may remain that are in fact snow covered, have a true type designation other than Ice/Snow, and are correctly retrieved as Ice/Snow but counted as mistyped in the table. Compared to the baseline results (Table 5-7), Dense, Moderate, Sparse, and Water CTPs are about the same but 13% of Barren cells are now misclassified as Ice. The snow cover/depth algorithm—which in practice will provide ice and snow detection inputs to the vegetation/surface type algorithm—uses a string of spectral and temperature threshold tests to minimize this type of misclassification.

Table 5-15: Confusion matrix for Mahalanobis classifier retrievals including Ice

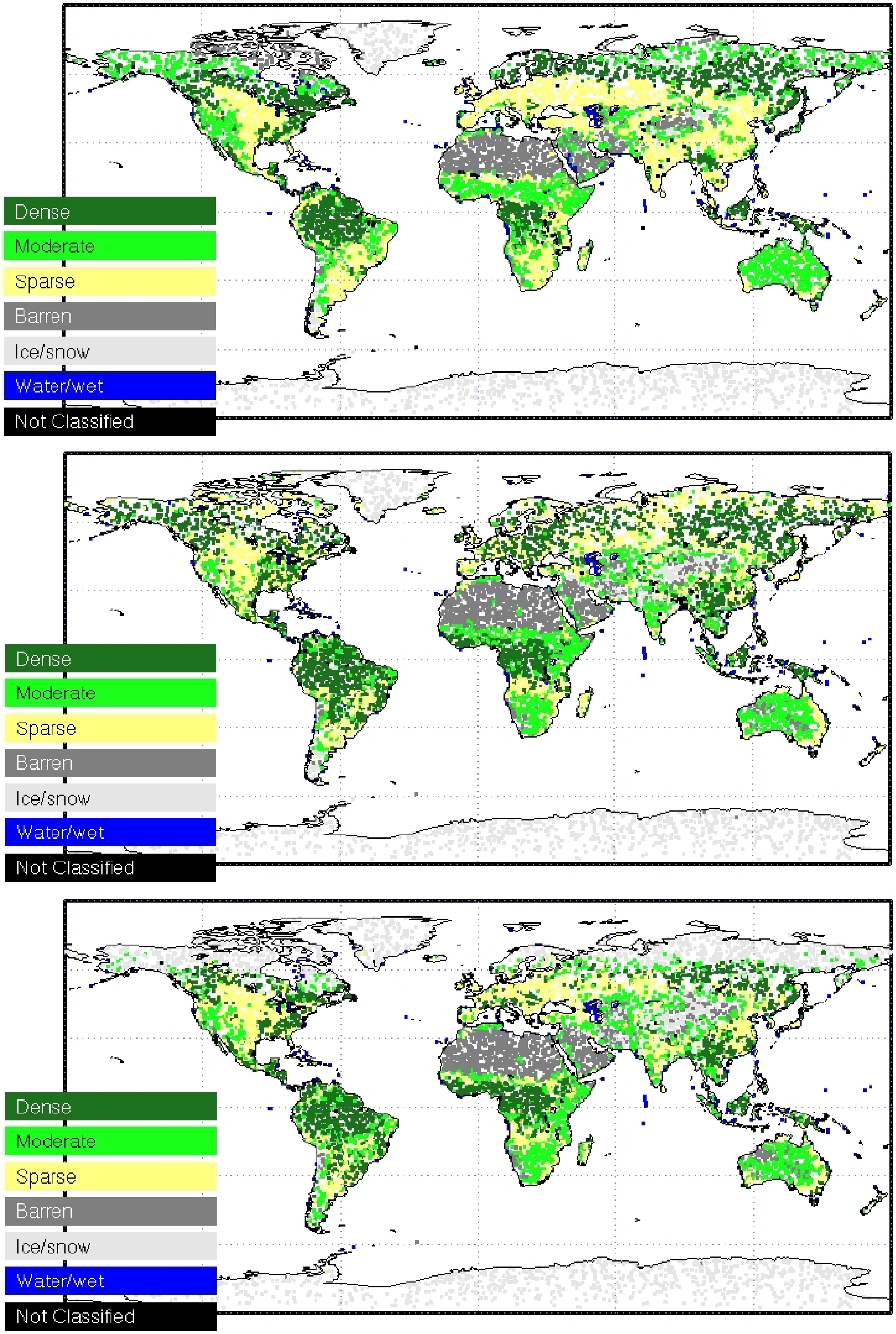
True type	% of cells that are in fact true type reported as							No. tested	% of total
	Dense	Moderate	Sparse	Barren	Ice	Water	Not Clsf'd		
Dense	69	11	14	0	3	0	3	8644	18
Moderate	24	39	20	9	5	0	3	12662	27
Sparse	19	28	41	3	2	1	5	13652	29
Barren	1	6	5	73	13	0	2	5318	11
Ice	1	1	1	1	93	3	1	5197	11
Water	1	5	3	1	3	80	7	1196	3
Not Clsf'd	16	19	18	11	14	6	15	1063	2
No. retr.	11790	10369	9930	5745	6928	1302	1668	47732	
% or total	25	22	21	12	15	3	3		

The following figures show the true and retrieved (July and October) vegetation/surface type maps. Here all 20,000 test points per month are typed and plotted revealing a significant snow cover detected in the October data. We do not test the accuracy of the snow cover retrieval (even in the table above) because 1) we are using monthly mean emissivities and therefore an accurate quantitative comparison to truth is not possible and 2) Ice type retrieval training is based solely on permanent ice cells (again because of the lack of adequate snow truth for this dataset) and therefore the algorithm's Ice spectral characteristics may not be representative of snow-covered land.

The maps demonstrate the accuracy and self-consistency of the retrievals and reveal the main areas of correspondence and disagreement with the truth and between the two months.

- The truth map has a large swath of type Sparse extending across most of Europe and east into much of China, Southeast Asia, and India. In Europe, the July retrieval returns mostly Dense and the October retrieval mostly Sparse consistent with the vegetation seasonal cycle. And both months return Dense or Moderate types in Southeast Asia where the true type is often Sparse.
- The two months are most consistent where seasonal changes are limited: Australia, the Tropics, Southern Africa, and the Sahara and Arabian deserts.
- The Sahel region south of the Sahara changes from Moderate type in the July retrieval to Sparse in October. This change may be consistent with seasonality, bearing in mind that the Sparse type is, as defined, a generally more highly vegetated type than Moderate.
- Snow appears in the October map at northern latitudes and in the July map at the tip of South America, which may also be consistent with seasonality there.
- Grasslands in the Great Plains, Patagonia in Argentina, and the Russian Steppe are correctly retrieved in both months. These areas are among the few where Sparse NPOESS types (grasslands, agriculture, and vegetation mosaic) completely dominate the landscape.

Figure 5-4: True type map (top) and July (middle) and October (bottom) retrievals



6. Algorithm Calibration and Validation Requirements

6.1. Pre-launch

To be completed.

6.2. Post-launch

To be completed.

6.3. Special considerations for Cal/Val

To be completed.

6.3.1. Measurement hardware

To be completed.

6.3.2. Field measurements or sensors

To be completed.

6.3.3. Sources of truth data

To be completed.

7. Practical Considerations

7.1. Numerical Computation Considerations

To be completed.

7.2. Programming/Procedure Considerations

To be completed.

7.3. Computer hardware or software requirements

To be completed.

7.4. Quality Control and Diagnostics

To be completed.

7.5. Exception and Error Handling

To be completed.

7.6. Special database considerations

To be completed.

7.7. Special operator training requirements

To be completed.

7.8. Archival requirements

To be completed.

8. Glossary of Acronyms

AMSR Advanced Microwave Scanning Radiometer

ATBD	Algorithm Theoretical Basis Document
AVHRR	Advanced Very High Resolution Radiometer
BT	Brightness Temperature [K]
CMIS	Conical Microwave Imaging Sounder
DEM	Digital Elevation Model
DMSP	Defense Meteorological Satellite Program
EDR	Environmental Data Record
EIA	Earth Incidence Angle
ESMR	Nimbus-7 Electrically Scanning Microwave Radiometer
FOV	Field Of View
IFOV	Instantaneous Field Of View
LST	Land Surface Temperature [K]
NPOESS	National Polar-orbiting Operational Environmental satellite System
RFI	Radio-Frequency Interference
RMS	Root Mean Square
RMSE	Root Mean Square Error
SDR	Sensor Data Record
SSM/I	Special Sensor Microwave/Imager
SSMIS	Special Sensor Microwave Imager Sounder
TB	Brightness Temperature
TMI	TRMM Microwave Imager
TOA	Top-of-Atmosphere (i.e., measured by sensor)
TRMM	Tropical Rainfall Measuring Mission
USGS	United States Geological Survey
VIIRS	Visible/Infrared Imager/Radiometer Suite
VIRS	Visible and Infrared Radiometer System (on TRMM)
VST	Vegetation/Surface Type
VWC	Vegetation Water Content [kg/m2]

9. References

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10. Appendix 1—Emissivity dataset

The following maps show selected emissivities from the Prigent dataset. Note that emissivities below and above—the dataset includes some emissivities greater than 1—the scale limits are plotted with the color scale end points.

Figure 10-1: 19H emissivities

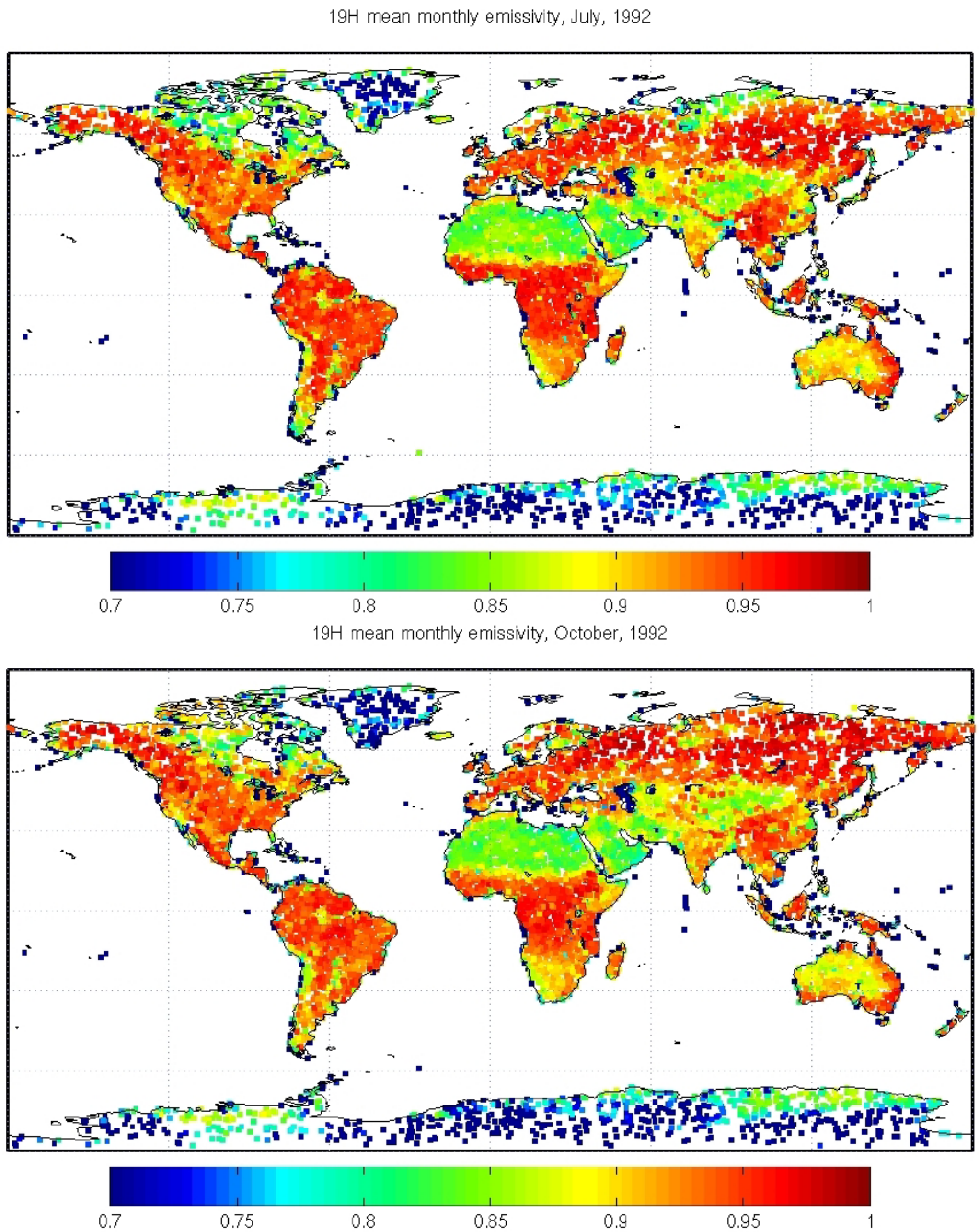


Figure 10-2: 19V emissivities

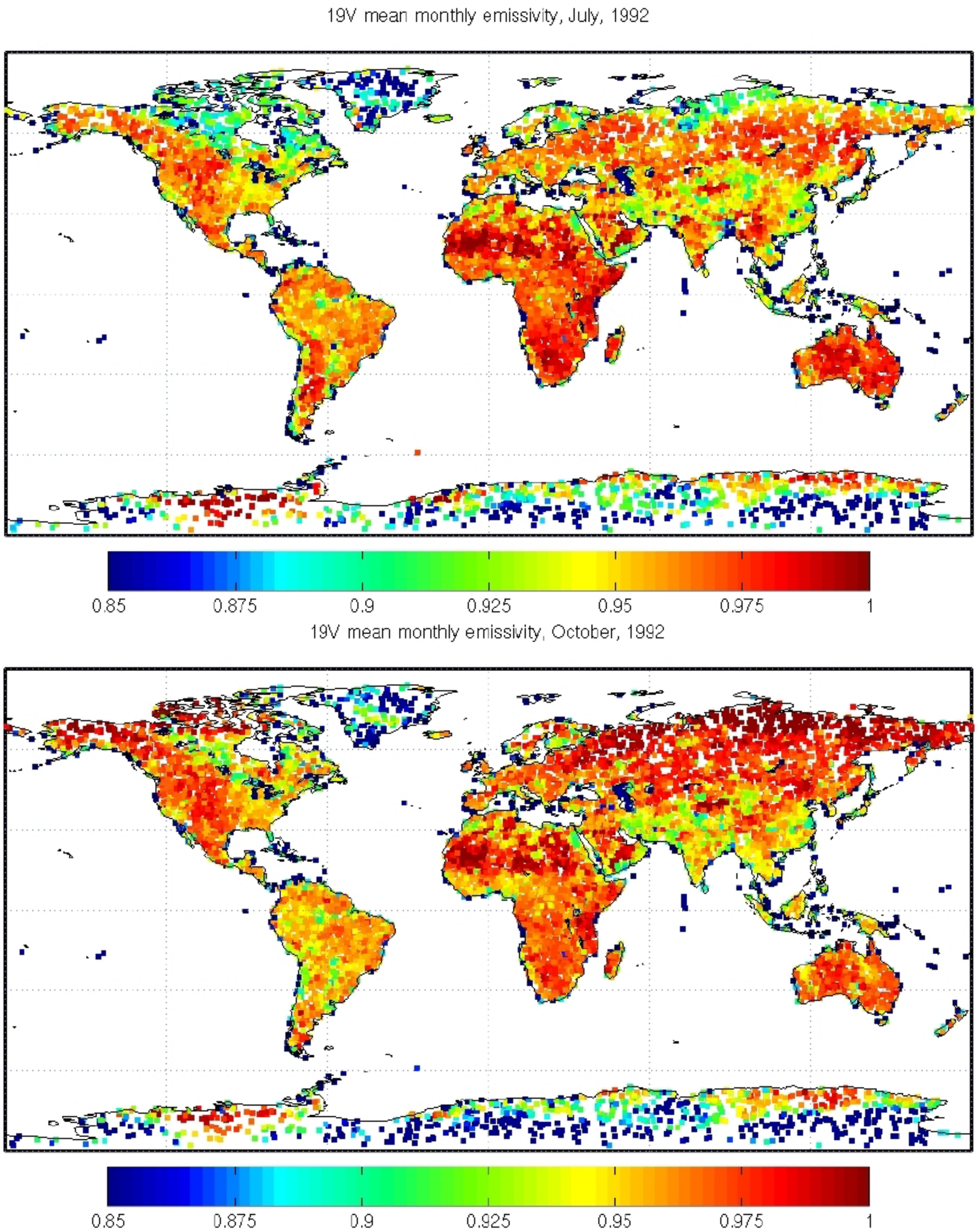
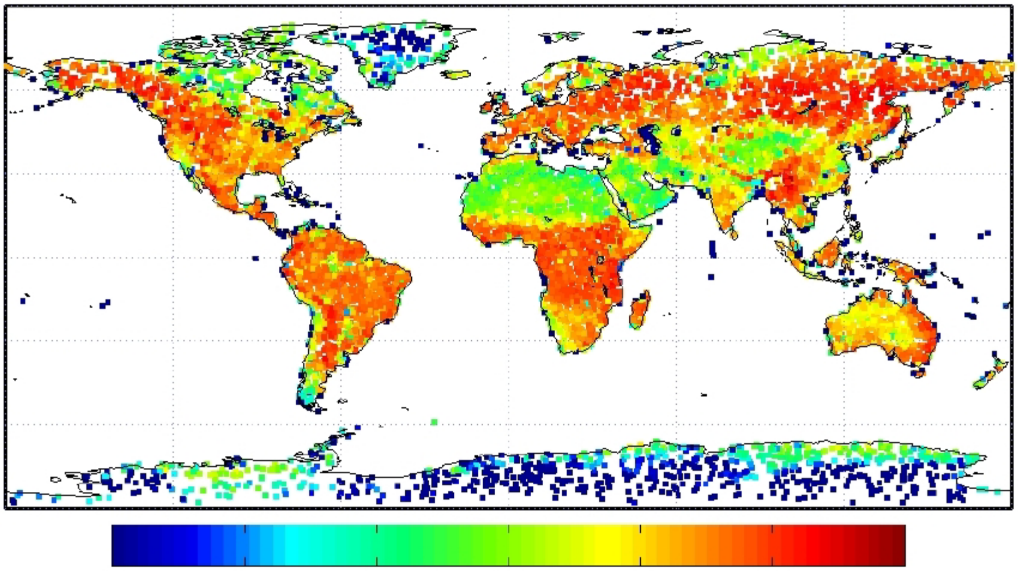


Figure 10-3: 37H emissivities

37H mean monthly emissivity, July, 1992



37H mean monthly emissivity, October, 1992

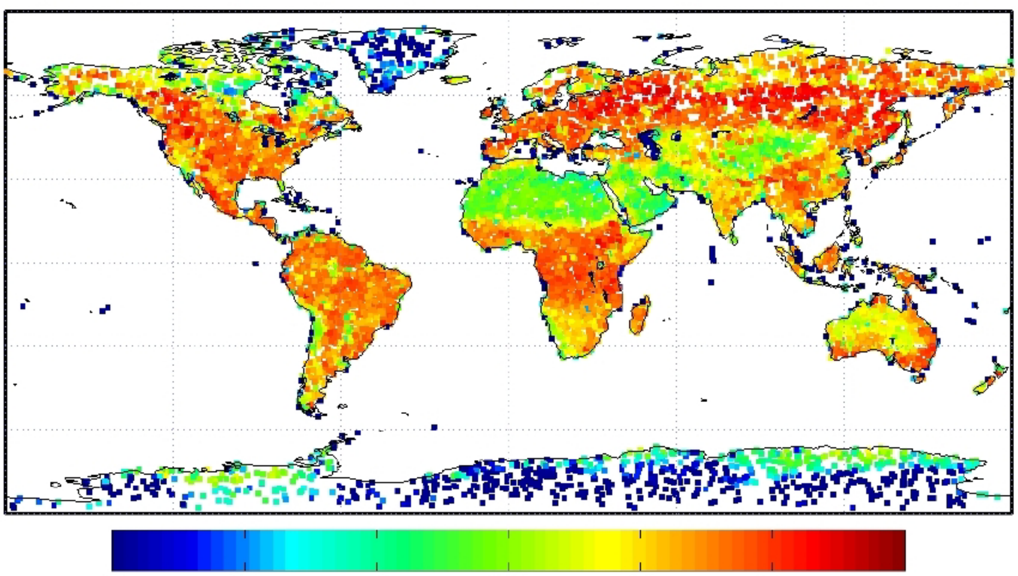
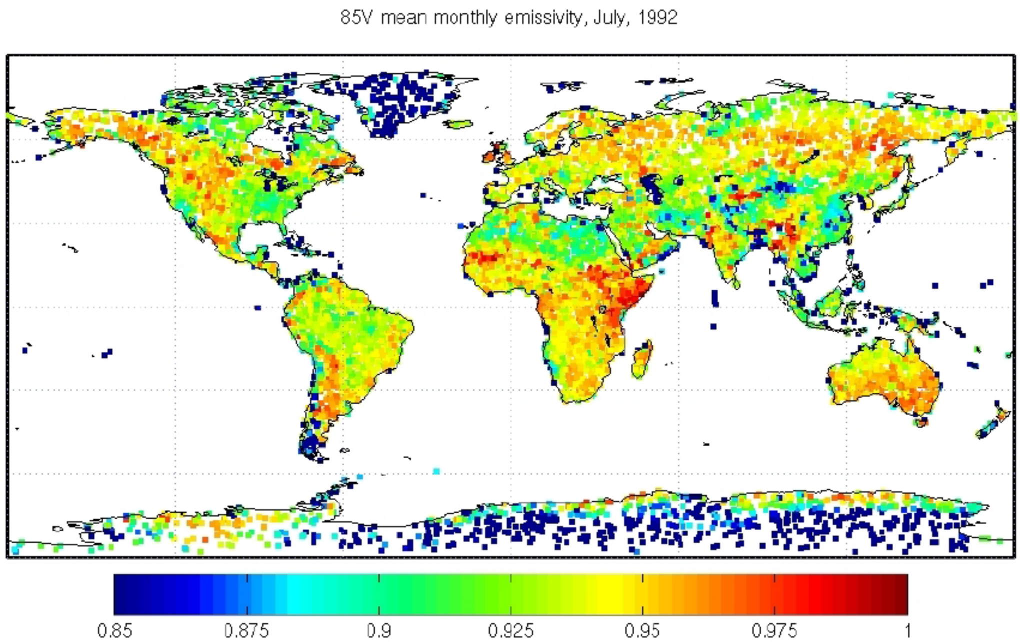
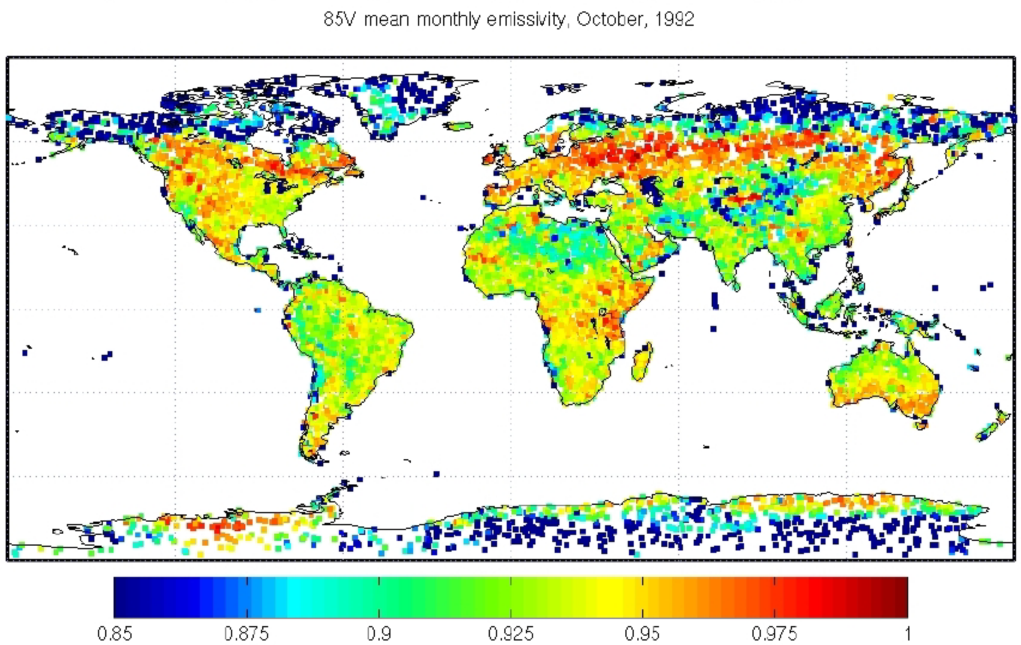


Figure 10-4: 85V emissivities





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